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Airline Travel Demand, the Derived Demand for Aircraft Fuel, and Fuel Utilization Forecasts Using Structural and Atheoretical Approaches

by

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ABSTRACT

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In the first chapter, we develop a dynamic model of collusion in city-pair routes for selected US airlines and specify the first order conditions using a state-space representation that is estimated by Kalman-filtering techniques using the Databank 1A (DB1A) Department of Transportation (DOT) data during the period 1979I-1988IV. We consider two airlines, American (AA) and United (UA) and four city pairs. Our measure of market power is based on the shadow value of long-run profits in a two person strategic dynamic game and we find evidence of relative market power of UA in three of the four city pairs we analyze.

The second chapter explores three models of forecasting airline energy demand: Trend line, ARIMA and Structural Model based on results from Chapter 1 and find that none of them is a dominant winner in American (AA) and United (UA) between Chicago and Salt Lake City.

In the third chapter, we use Model Averaging and Forecast Combination Techniques

to provide a decisive conclusion focusing on discussing Equal Weighted Averaging, Mean Square Weighted Averaging and Optimized Weighted Averaging on UA and AA in City-Pairs Chicago -Seattle and Chicago-San Diego.

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Chapter 1[1]

A Dynamic Model of Airline Competition

1.1. Introduction

In this dissertation we analyze a number of issues pertaining to one of the most important transportation industries in the U.S., the commercial airline industry. The industry has continued to consolidate since it was deregulated in 1978, and we develop a structural dynamic competition model to better understand how one could evaluate if such consolidation has led to anticompetitive behavior on the part of firms competing in thin competitive markets, specifically particular city-pairs in which there is limited competition and possibly limited scope for the competitive fringe to force firms to price as perfect competitor would. We also are interested in one of the most important of the inputs to the airlines, their fuel needs, specifically turbo fuel. The U.S. commercial airline industry consumes 4% of the fuel used in the U.S. and understanding what influences the demand for fuel and how to best forecast the airline industry's future energy demands has import to the carriers themselves, for planning and operational decision, but also for world energy markets. We thus turn our focus on the use of our structural model for purposes of forecasting energy demands. Energy demands for commercial airlines have been addressed by Greene (1997), Faquih (2008) and etc. but none have used a structural

[1] Chapter 1 is based on Fang, Ying and Sickles, Robin C. (2007) and Fang, Ying and Sickles, Robin C. (2008a)

model as ours. We also discuss and utilize various forecasting approaches that combined forecasts using various weighting schemes and we utilize these as well as specific forecasts from our structural model, ARIMA time series and simple time trends. A combined estimate or forecasts provide a decisive conclusion instead of a confusion of diversified results.

1.2. Aviation Industry

The aviation industry is defined as the design, manufacture, use, or operation of aircraft; the term aircraft refers to any vehicle capable of flight. Aircraft can either be heavier than air or lighter than air. Lighter than air craft includes balloons and airships, and heavier than air craft include airplanes, autogiros, gliders and helicopters.

As early as 400 BCE, the Greek scholar Archytas, built a wooden pigeon that moved through the air, which is the earliest aviation experiment. The American Orville Wright and Wilbur Wright are generally credited with making the first controlled, powered, heavier-than-air human flight on December 17, 1903. In 1905 Charles and Gabriel Voisin, two French fliers, started the world's first aircraft company. The military value of aircraft was quickly recognized during World War I (1914-1918), and production increased significantly to meet the rising demand. More powerful motors, enabling aircraft to reach speeds of up to 130 miles per hour, were developed. After World War I, thousands of military planes were converted to civilian use. By 1917 the U.S. government adopted something totally new, airmail. The Contract Air Mail Act of 1925 was the first major legislative step toward the creation of the private U.S. airline industry. Henry Ford, the automobile manufacturer, jumped into aircraft manufacturing and produced one of the first all-metal planes. On May 21, 1927, the pilot Charles Lindbergh flew across the Atlantic Ocean. This event made aviation an established industry by attracting millions of private investment dollars. For the airlines to attract more passengers away from the railroads, larger, faster, and safer airplanes were needed, and aircraft manufacturers responded to the challenge. There were so many improvements to aircraft in the 1930s that many people believe it was the most innovative period in aviation history. Newton's Third Law theorizes that a rearward-channeled explosion can propel a machine forward at a great rate of speed. The British pilot Frank Whittle applied this law to the first jet engine in 1930. During World War II, aircraft production became the world's leading manufacturing industry.

Aviation is broadly grouped into three categories: general aviation, air transport aviation, and military aviation. By 1947 all the basic technology needed for aviation had been developed, including jet propulsion, aerodynamics, and radar. Civilian aircraft orders drastically increased from 6,844 in 1941 to 40,000 by the end of 1945. Among the minor military contractors was the Boeing Company, which later became the largest aircraft manufacturer in the world. With all the new technologies developed by this time, airliners were larger and faster, and featured pressurized cabins. New aerodynamic designs, metals, and power plants resulted in high – speed turbojet airplanes. By 1950 the airliner was well on the way to replacing the railroad and the ocean liner as the primary means of long-distance travel. The economic, social, and political consequences included the creation of global markets, opportunities for global travel undreamed of a generation before, and increasing cultural homogeneity.

In 1938 the Civil Aeronautics Authority, an independent regulatory bureau, was developed. The airline industry resembled a public utility, with a government agency determining the routes each airline flew and overseeing the prices charged. On October 24, 1978, the Airline Deregulation Act was approved. The industry became market – driven, with customer demand determining the levels of service and price. A major development that followed deregulation was the widespread development of hub – and – spoke networks, which enable the airlines to serve far more markets than they could with the same size fleet if they offered only direct, point – to – point service. Another important development following deregulation was the advent of computer reservation systems. These systems help airlines and travel agents keep track of fare and service changes, which occur rapidly. The systems also enable airlines and travel agents to efficiently process the millions of passengers who fly each day. In manufacturing, several mergers in the 1990's led to the disappearance of several historic U. S. airplane builders, such as McDonnell Douglas, which merged into Boeing. International partnerships became increasingly significant, with Airbus capturing one-third of the world market in jet airliner sales in the 1990's.

A number of researchers examined the impact of the 1978 Deregulation Act on the productivity of U.S. carriers and the demand for their services as well as how the international deregulation of the industry that accelerated in the ensuring years impacted the supply and demand for airline service world-wide. The studies pointed to an increase in efficiency of airline carriers due to increased competition, a provision of more service at lower prices, and an eroding of service quality as carriers competed on the basis of price instead of on the basis of in flight amenities and flight frequency with relative low load factors. Johnson (1991) believes that deregulation did not decrease airline employees' earnings, but increased union expenditures.

On Sep. 11, 2001, terrorists hijacked four commercial airplanes and deliberately crashed two into the towers of the World Trade Center in New York City and one into the Pentagon building in Washington, D.C. The fourth hijacked plane crashed in Somerset County, Pennsylvania. After the hijackings, U.S. airports and airlines sought new ways to protect against terrorist attacks. Congress passed legislation requiring federal employees to handle all passenger and baggage inspection in U.S. airports by the end of 2002.

Fears of terrorism and a sluggish world economy contributed to a decline in air travel in the early 2000's. In 2003, British Airways and Air France discontinued all Concorde flights because the flights were no longer profitable.

Although many countries continue to operate state-owned airlines, most large airlines in the early twenty-first century are privately owned and therefore governed by microeconomic principles to maximize shareholder profits. The airline industry as a whole has a cumulative loss during its history, once subsidies for aircraft development and airport construction are included in the cost. The lack of profitability and continuing government subsidies are justified with the argument that positive externalities, such as higher growth due to global mobility, outweigh microeconomic losses. A historically high level of government intervention in the airline industry can be seen as part of a wider political consensus on strategic forms of transport, such as highways and railways, both of which are also publicly funded in most parts of the world.

U. S. airlines face substantial upheavals in the forms of mergers, failures, bankruptcy filings, reorganizations, and operating loss reports. This situation has raised concern that the future is bleak in terms of the number of carriers that will survive and prosper. Profitability is likely to improve as carriers find ways to be more cost - efficient and more competitive low-cost carriers proliferate.

1.3.Characterizing the Market for Airline Travel Demand

We develop a dynamic model of collusion in airport-pair routes for selected U.S. airlines. What is City Pair and why is City Pair? In Airline bookings, City Pair is the departure and arrival cites on an itinerary. The number of city pairs served by an airline is sometimes used as a measure of its size. In the vast empirical economics literature on the airline industry, researchers typically study the impact of characteristics of an airline market on market outcomes. In order to carry out such studies, researchers must first make a choice: How to define the market? City Pair has been approved to be the best approach. Many empirical papers in the literature use the airport-pair approach to market definition. These studies include several early studies exploring the effect of market structure and competition on airfares following deregulation, (for example, Borenstein (1989, 1991), Brueckner, Dyer and Spiller (1992) or Brueckner and Spiller (1994) and numerous studies of the competitive effects of international alliances and antitrust immunity (e.g., Brueckner and Whalen (2000), Brueckner (2003), and Whalen (2007). The city-pair approach is followed by an alternative set of papers, including studies of competition and airfares by Berry (1990), Evans and Kessides (1993,1994), and Berry, Spiller and Carnall (2006), studies of the impact of airline mergers (e.g., Werden, Joskow and Johnson (1991), Peters (2006)), studies of low cost carrier entry (e.g., Bogulaski, Ito and Lee (2004)), as well as numerous studies of domestic code sharing (e.g., Bamberger, Calton and Neumann (2004), Ito and Lee (2007) and Gayle(2008). Finally, another set of studies that examine the effect of low cost carrier presence on market fares (e.g., Morrison(2001), Goolsbee and Syverson (2008), Brueckner, Lee and Singer (2010)) use airport-pairs as the unit of observation, but allow for the impact of competition at the city pair level by explicitly modeling competitive effects from adjacent airports within a metro area. Berry (1992) considers the effect of an airline's scale of operation at an airport on the profitability of City Pair. Market definition is also a crucial factor guiding government regulatory decisions regarding the airline industry. For example, in evaluating proposed airline mergers, the post merger level of competition in airline market is a key concern. The competition analysis on a city-pair level can answer these kinds of question and give meaningful guidance to the government and to the public. With city-pair approach, we are able to exam airline industry in a more micro-analytic way.

In earlier work on collusion and market power Roller and Sickles (2000) estimated a two-stage static structural model in which the firms play a repeated sequence of one-shot capacity and pricing games. They found that the market conduct parameter, whose value can differentiate among Bertrand, Cournot-Nash, and monopolistic equilibrium, had adjusted to a value closer to a competitive equilibrium as the industry was deregulated. Using a somewhat different time series approach Alam and Sickles (2000) looked at market conduct on the supply side (focusing on the degree of inefficiency) and found that a similar convergence to competitive equilibrium took place in the U.S. airline industry after its deregulation in 1976. Captain and Sickles (1997) utilized a one-stage static structural model of market conduct for the European airlines in which labor choices were endogenous and where firms play a pricing game and estimated conduct to be between a competitive and Betrand solution. Unfortunately, these studies relying on the conjectural variations approach are myopic to the past and are not forward-looking when current actions are considered. Puller's (2007, 2009) models introduce dynamics in order to provide more realism in modeling dynamic decision making in the conduct parameter framework. While in the former model the reason for dynamics is fundamental (capacity choice), for the latter model it is strategic (repeated game).

The models we specify and estimate in this chapter are based on the realistic assumption that firms consider the future when they make a current decision and that decisions they make today will influence outcomes in the future. In this sense it is similar in spirit to the work of Captain et al. (2007), although they did not estimate but rather calibrated their model. In this chapter we consider models that also allows for more flexibility in describing how equilibrium outcomes can be characterized. Solutions are not necessarily at the nodes of the solutions identified by the static market conduct approaches. As pointed out in Perloff et al. (2007), dynamic strategic considerations also often require new methods of estimation, such as the state-space methods which we employ herein, instead of the standard nonlinear least squares. Specifically, this chapter develops a dynamic model of collusion in city-pair routes for selected US airlines and specifies the first order conditions based on a state-space representation that is estimated by Kalman-filtering techniques (1960). Our model controls for economy-wide exogenous variables and city-pair specific variables. We examine two U.S. commercial airline firms, United and American Airlines between 1979I and 1988IV.

After the Airline deregulation Act of 1978 the airline industry moved from service-based to price-based competition. Carriers were able to set their own fares, select and drop routes, and control flight frequency. U.S. airlines continue to face substantial upheavals in the form of mergers, failures, bankruptcy filings, reorganizations, and operating losses. As the concentration of the industry continues to increase and as the number of profitable incumbents continues to dwindle, as fuel prices continue to soar, the survivability and prosperity of incumbents becomes increasingly problematic. In this economic and institutional setting the dynamics of strategic decision making involving various forms of collusion in the form of formal alliances are important to understand. Another empirically attractive feature of this industry, a consequence of the strict filing requirements imposed by the federal government, is the wealth of accessible data not generally available in most other industries.

Before looking at the market power and the dynamics of airline carriers' interaction, we present and compare the traditional and new empirical models of market power -- the ability to raise price above marginal cost. We review the literature and methods to date, and focus particularly on dynamic models. Research on market power is important for both policy makers and academics. It provides evidence that policy makers can use to improve antitrust and merger laws. It also allows academics to test theoretical models.

Mason's (1939, 1949) structure-conduct-performance approach is the traditional one to empirical studies of market power. It holds that an industry's performance depends on the behavior of sellers and buyers, which depends on the structure of the market. The structure is summarized by the number of firms and the market shares.

The modern static approach attempts to estimate the market power and to determine its causes by estimating optimality and other equation simultaneously. Bresnahan (1989) summarized most of the modern static approaches through the 1980's.

There are three major types of modern static models, which are based on a single-period oligopoly model.

Structural Models for Homogeneous Products

The structural approach has two key advantages: providing a direct estimate of market power and simulating the effects of changes in the market as long as the changes do not affect the market structure. Structural models have been used to simulate the effects of mergers on price: Werden and Froeb (1994), Slade (1998), Nevo (2000), and Hausman and Leonard (2005). Its main disadvantage is that the results depend on a variety of assumption on functional forms, distributions, and other facts that are not generally know to the econometrician.

Comparative Statics for Homogeneous Products

Suppose that firms face a constant marginal cost. A shock causes the marginal cost to rise. In Sumner (1981), Sullivan(1985), Ashenfelter and Sullivan (1987), a change in the tax rate or difference in the tax rate across states allows them to conduct a comparative statics experiment. If the market is competitive, the price will increase by the same amount as the marginal cost. Thus in principle, we can test for noncompetitive behavior by checking whether price moves disproportionately with marginal cost.

Extended Structural Models for Differentiated Products

In recent years, extended structural models for differentiated products allow us to examine richer questions: for example, constructing and testing a model of Stackelberg behavior since we can separately model the behavior of the individual firms in the market.

The first major approach is to estimate the residual demand facing each firm. Starting from the multi-firm structural model, one derives an inverse residual demand function that is conditional on the firm's own quantity, structural demand variables, industry factor prices, other firm's cost variables, and other firms' behavioral parameters.

Bresnahan (1981a, 1987), Baker and Bresnahan (1988), Spiller and Favaro (1984), Suslow (1986), Gelfand and Spiller (1987), and Slade (1987) are important examples of residual demand or other differentiated product studies.

The second approach is to estimate the full system of demand and optimality equations by a neoclassical demand model. A few of the best-known studies include Bresnahan (1981, 1987) and Hausman (1997). In this approach, a system of demand equations is estimated using restrictions from economic theory. Based on these estimates and some information about cost curves, the econometrician then uses the estimated elasticities of demand to determine the degree of market power.

In the other approach, consumer or other micro-data are used to estimate consumer demands. The best-known studies using this approach employ a random utility model. A widely used approach to estimating the demand elasticity is to use a linear random utility model from Perloff and Salop (1985) and Anderson, de Palma, and Thisse (1992).

Some of the best-known applications of this approach to estimate market power in a differentiated goods market are Berry et al. (1995), Goldberg (1995), Nevo (2001), and Pinske et al. (2002). Berry et al. (1995) estimate automobile demand system using product-level price and quantity data. Their demand estimates reflect the sum of individual purchase probabilities. Goldberg (1995) uses household-level, new car purchasing data to estimate the probabilities that a household purchases a given model. She then uses these household probabilities to determine the demand curve that firms face. Nevo (2001) decomposes his estimated price-cost margins into margins due to product differentiation, multi-product firm pricing, and potential price collusion. He concludes that the first two factors explain most of the observed price-cost differentials. Pinske et al. (2002) provide an alternative approach where the differentiation is due to spatial competition. They use a semi-parametric approach to estimate cross-price response coefficients.

Compared to the aggregate structural model, a key advantage of all these models is better estimates of the demand and optimality equations, allowing own- and cross-elasticities to vary across brands, which presumably results in more reliable demand estimates in the real world.

Until now, we have discussed estimating market power under the assumption that firms engage in a sequence of static games: In each period, a firm maximizes its current profit given its belief about how its rivals behave and assuming that actions in other period do not affect behavior in this period. We now examine how to model games in which firms interact over many periods: where they play a dynamic game. Each firm maximizes its expected present discounted value of the stream of current and future profits. When each firm solves a dynamic optimization problem where its payoff depends on the behavior of other firms, the industry equilibrium is the solution to a dynamic game. We distinguish dynamic game between two types of reasons: strategic and fundamental. If dynamic interactions arise because firms think that their rivals' will respond in the future to their current action, we say that the reason is strategic. If a firm solves a dynamic rather than a static problem because its current decision affects a stock variable that affects its future profits, we say that the reason for the dynamics is fundamental.

We examine environments in which the only reason for dynamics is strategic. We start by reviewing the basic concepts from game theory involving many period games, including subgame perfection and Folk theorem of supergames. A subgame is a game begins with a particular history. An equilibrium is subgame perfect if the set of decision rules constitute an equilibrium for any possible history, that is, for any possible subgame, not only for the subgames that arise in equilibrium. The Folk theorem of supergames states that if players are sufficiently patient, discount factor is sufficiently close to 1, then any feasible, individually rational payoff can be supported in a subgame perfect equilibrium (Fudenberg and Tirole 1993, Chapter 5.1). A payoff is individually rational if it is greater than or equal to the minimum payoff that a player can guarantee.

There are two different approaches to formulating empirical models based on repeated games. The first approach assumes that firms use trigger strategies, and the second assumes that firms use strategies that are continuous in the history.

The models proposed by Rotemberg and Saloner (1986) and Green and Porter (1984) are examples of repeated game models that provide a basis for estimation. Both these models assume that tacit cooperation is supported by the threat of reversion to non-cooperative actions: firms use trigger strategies. The extent of the cooperation changes randomly, due to the presence of random shocks. Firms use a simple punishment strategy: they behave "cooperatively" as long as their rival has behaved cooperatively in the past. Cheating by any firms causes all firms to use the non-cooperative Nash equilibrium price (of the one-shot game) at every period in the future. The assumption that the demand shocks are uncorrelated is important, because it implies that the cost of cheating is the same in each state of nature. Kandori (1991) and Haltiwanger and Harrington (1991) study the model with correlated demand shocks. Porter (1983) and Lee and Porter (1984) test variations of the Green and Porter model using U.S. railroad pricing data from the 1880's. Their results are consistent with Green and Porter (1984) model of trigger strategies. Hajivasilious (1989) reaches similar conclusions. However, Town (1991) finds that price wars were not related to demand fluctAAtions. This finding is contrary to the predictions of both the Green and Porter (1984) and the Rotemberg and Saloner (1986) models. Domovitz et al. (1987) find little evidence of price wars either in booms or recessions. Suslow (1998) presents evidence that conflicts with the predictions of the Rotemberg and Saloner (1986) model. In an examination of pre-World War II cartels, she finds that a cartel is more likely to break down during recessions and depressions. Recent theoretical developments have built on the Rotemberg and Saloner and the Green and Porter models. For example, Athey et al. (2004) study an infinitely repeated Bertrand game in which firms receive independent and identically distribution cost shocks. Using a two-player game in which firms imperfectly monitor their rival's actions, Matsushima (2004) shows that the collusive outcome can be sustained when the discount factor is close to one.

In the trigger strategy models, certain observations, such as low sales or a low market price, trigger a temporary or permanent breakdown in cooperation. These strategies are discontinuous in the history: a small difference in the history can lead to a large difference in behavior. An alternative is for firms to use strategies that are continuous in the history. With these strategies, a small deviation from cooperation causes a small change in the history, and leads to a small punishment. Slade (1989) models a price-setting game with continuous reaction functions. The equilibrium with continuous reaction function is "approximately" subgame perfect when the discount factor is larger. In this equilibrium firms never cheat and they never need to punish each other. However, random demand shocks mean that there are periods where firms are groping towards a new equilibrium as they learn the new demand parameters.

We now focus on games in which dynamics arise because of changes in economic fundamentals. This type of game is often referred to as a dynamic game or a stochastic game. There are two major fundamental sources of dynamics: production and demand.

The firms' factors of production are variable, fixed, or quasi-fixed, depending on the cost of changing their level. When production involves quasi-fixed inputs, a firm needs to solve a dynamic optimization problem, regardless of the market structure. A growing empirical literature attempts to estimate adjustment costs and to distinguish between variable and quasi-fixed inputs in competitive markets: Pindyck and Rotemberg (1983), Epstein and Denny (1983), Hayashi and Inoue (1991), Luh and Stefanou (1991), Frenandex-Cornejo et al (1992), Anderson (1993), Burh and Kim (1997), Hall (2002). Advertising and consumer switching are two reasons why current demand may depend on past actions, so that firms operate in a dynamic environment. Advertising can create a stock effect. Current advertising may have long-lasting effects by increasing the number of the firm's customers today and in the future. The value of current advertising depends on the current stock of potential customers. The link between the optimal decisions in different periods makes the firm's problem dynamic.

Most applications of dynamic games assume that agents use either open-loop or Markov decision rules. Open-loop Nash equilibrium rules are time consistent, but typically not subgame perfect. With open-loop strategies, we can nest a family of equilibria, including competitive, non-cooperative Nash and collusive equilibria. Markov Strategies are decision rules that depend only on the directly payoff-relevant state variable. A subgame-perfect Markov equilibrium is referred to as a Markov perfect equilibrium (MPE). The past ten years has been an explosion of papers that estimate Markov perfect equilibria. Recent papers, including Pakes et al. (2004) and Bajari et al. (2004), provide new estimation methods and reviews of earlier work. This estimation strategy can be modified so that it permits the identification of the industry structure. That is, it enables the researcher to test whether firms are playing a non-cooperative game, acting collusively, or behaving as price takers.

A conjectural variation or a market conduct parameter model is used to estimate market structure under the assumption that the equilibrium is either open loop or Markov perfect. This model requires that the single-period payoff is a quadratic function of the state and the control variables that the equation of motion is linear in those variables, and that agents use linear decision rules. Under these restrictions, we can solve the equilibrium conditions in closed form to obtain the decision rules, which are linear in the state variables.

Golan, Karp and Perloff (1998, 2000) developed a framework for modeling an oligopolistic game over a discrete action space. This approach allows us to use sample data as well as the game-theoretic first-order conditions to estimate pure or mixed strategies for each one of the players. They then formulated three models to solve the firms' strategies. The first one is a simple ME-ML (maximum entropy-multinomial logit) that cannot incorporate the game theoretic restrictions into the estimation process. The second one is the multinomial GME which is more efficient than the first model but also did not incorporate the game-theoretic restrictions. The third model is the GME-Nash model that provides a simple framework for a simultaneous estimation of both firms' strategies while taking into account all of the available data and the game-theoretic conditions.

1.4. A New Dynamic Structural Model of Airline Travel Demand

Now, let's discuss rationale for collusion and market power. Standard economic theory predicts that under mild assumptions when there are only a few agents on one side of a market those agents will often possess market power---the ability to alter profitably prices away from competitive levels without losing all customers to competitors. The Cournot model of duopoly assumes that a firm never had to consider the reaction of its competitor to its price or quantity choice. In the Bertrand model, a firm could undercut its rival's price at the margin and compete-away all of the rival's customers. In practice, however, a firm may recognize that if it undercut its rival the rival will respond by cutting its own price, ultimately leading to a short-run gain in sales but a long-run reduction in the price level.

Consider a dynamic model in which these concerns arise. Each firm i attempts to maximize the discounted value of profits, $\Sigma_{t=1}^{\infty}\beta^{t-1}\pi_{it}$, where π_{it} is firm

i 's profit in period t . If each firm initially charges p^m , the monopoly price, then industry profit is maximized. It continues to charge p^m in period t if in every period preceding t both firms have charged p^m ; otherwise it sets its price at marginal cost c forever. This is equilibrium if the discount factor is sufficient high. In charging p^m the firm earns half the monopoly profit in each period. By deviating from this price, a firm can earn maximum profit, Π^m , during the period of deviation but it receives zero forever. Therefore, if $\frac{\Pi^m}{2}(1+\beta+\beta^2+...)\geq\Pi^m$, if $\beta\geq\frac{1}{2}$, then these strategies are equilibrium ones, which are also called trigger strategies. There are many other equilibria in this game, any price between the competitive price and the monopoly price can be sustained as an equilibrium price as long as the discount factor is greater than $\frac{1}{2}$. The Folk Theorem summarizes this outcome: in an infinite repeated game, any feasible discounted payoffs that give each player, on a per-period basis, more than the lowest payoff that he could guarantee himself in a single play of the simultaneous-move component game can be sustained as the payoffs of an subgame perfect Nash equilibrium if players discount the future to a sufficiently small degree.

Now, let's discuss rationale for Dynamic Decision Making. Beginning with the classic work of Chamberlin (1929), researchers have continued to explore the implications of repeated interaction between collusive oligopolists as well as factors that may hinder such collusion in repeated pricing games. Consider a small number of identical firms producing a homogeneous product. Chamberlin conjectured that the firms in the industry would charge the monopoly price. Each firm makes profit Π^m / n , where $\Pi^m \equiv \Pi(p^m)$. As Chamberlin noted, detection lags and asymmetries between firms are two factors that may hinder collusion. Tacit collusion is enforced by the threat of retaliation. But retaliation can occur only when it is learned that some member of the industry has deviated. For example, before the existence of online travel companies, the prices charged by airlines may be somewhat hidden. But in the current environment, and to some degree in the environment that existed during our sample period, the prices charged by an airline can be observed fairly quickly by its competitors.

Oligopolists are likely to recognize that one threat to collusion is lack of secrecy and consequently may take steps to control it. An example is Orbitz, which is an online travel company funded by five airlines, American, Continental, Delta, Northwest and United. Under asymmetric conditions, the oligopolists' marginal costs may differ and thus they have different monopoly prices. Low-cost firms would prefer to coordinate on a lower price than the higher-cost firms. Theory suggests that as an industry becomes more competitive, it becomes more important for a firm to perform efficiently relative to other firms if it is going to survive. This is one of the sources of dynamic productive efficiency revealed in the U.S. airline industry after deregulation by Alam and Sickles (2000). But, how does market power for airlines arise? Do they arise from barriers to entry, from sunk costs of gate and slot access, scale and network economies, or from hub-and-spoke systems which can give carriers market power even on relatively competitive routes? Borenstein (1989), among others, has estimated the importance of route and airport dominance in determining the degree of market power exercised by an airline. His results indicate that an airline's share of passengers on a route and at the endpoint airports significantly influence its ability to mark up price above cost. The high markups of a dominant airline, however, do not create much of an "umbrella" effect from which carriers with smaller operations in the same markets can benefit. Other rationale for market power on routes come from Berry (1992) who pointed out that airline firms are suited to serve different routes by virtue of unobserved heterogeneities (market niches) that allow them to exploit monopoly power over their differentiated product. An alternative view is found in the work of Morrison and Winston (2000) who examine merger activity and the factors that influence them for the U.S. airlines. They make the empirical argument that mergers are not driven by a desire to obtain market power but rather by the acquiring carriers' desire to expand their international routes. These routes tend to be more profitable on average than domestic routes because of bilateral agreements that limit entry. Moreover, the acquired carriers often have strong incentives to merge because of poor financial prospects (Crandall and Winston, 2006). There is a substantial body of literature that has examined the reasons for and against the presence of market power in the commercial airline industry. What we consider below is an econometric model that can provide evidence for or against such market power in a dynamic setting of strategically interacting carriers at a level of disaggregation that provides us the best empirical measures of such potential conduct, which is the city pair route.

Most existing methods for estimating market power are based on the assumption of a static equilibrium and use standard econometric techniques, such as ordinary least squares and instrumental variables. Most previous literature estimates only the degree of market power and ignores the role of strategies. This chapter examines dynamic models of oligopoly. This research is important. It provides evidence that can be used by policy makers in devising optimal antitrust laws. It can be used in court cases. It also allows academics to test theoretical models that were previously accepted on faith. Previous literature mainly focused on answering two questions: How much market power do firms have? What factors (such as barriers to entry) determine market power? This chapter adds one more discussion: what strategies do firms use and how do these strategies affect market power?

We frame the model as a dynamic programming problem, Firm1-AA's dynamic program is

$$J^1(q^1_{c,t-1}, q^2_{c,t-1}, x_t, z_t) = \max p^1_{c,t} q^1_{c,t} - c^1(q^1_{c,t}) + \beta J^1(q^1_{c,t}, q^2_{c,t}, x_{t+1}, z_{c,t+1})$$

on choosing output $q^1_{c,t}$. While for Firm2-UA, its dynamic program is

$$J^2(q^1_{c,t-1}, q^2_{c,t-1}, x_t, z_t) = \max p^2_{c,t} q^2_{c,t} - c^2(q^2_{c,t}) + \beta J^2(q^1_{c,t}, q^2_{c,t}, x_{t+1}, z_{c,t+1})$$

on choosing output $q^2_{c,t}$, where β is the discount factor, the c subscript refers to an city pair, the t subscript is the time period, x_t are economy-wide exogenous variables, and $z_{c,t}$ are city-pair specific exogenous variables. The parameter β is at 0.90 in our analysis below.

There are a variety of ways that we can allow the exogenous variables to influence the shadow value of $q^1_{c,t}$. We outline three different methods. First, we can write the first-order condition for AA (Firm1) as

$$p^1_{c,t} + q^1_{c,t}\frac{\partial p^1_{c,t}}{\partial q^1_{c,t}} - \frac{\partial c^1}{\partial q^1_{c,t}} + \alpha^1_{c,t}D_c + \beta(\lambda^{11}_t q^1_{c,t} + \lambda^{12}_t q^2_{c,t} + \lambda^{13}_t x^1_{t+1} + \lambda^{14}_t z^1_{t+1}) = 0$$

and the first-order condition for UA (Firm2) as

$$p^2_{c,t} + q^2_{c,t}\frac{\partial p^2_{c,t}}{\partial q^2_{c,t}} - \frac{\partial c^2}{\partial q^2_{c,t}} + \alpha^2_{c,t}D_c + \beta(\lambda^{21}_t q^1_{c,t} + \lambda^{22}_t q^2_{c,t} + \lambda^{23}_t x^2_{t+1} + \lambda^{24}_t z^2_{t+1}) = 0$$

where D_c is a dummy for the particular city pair c. The above two equations are the measurement equations which will be used in the Kalman filters. Below is a complete discussion of how the Kalman filter is set up for this problem.

Shadow price calculation is an important by produce of the dynamic program and is useful in analyzing equilibrium strategies and market power. Let's first look at a simplest optimization problem --- two variables and one equality constraint:

max $f(x, y)$

subject to

$h(x, y) = a$

Let f and h be C^1 functions of two variables. For any fixed value of the parameter a, let $(x^*(a), y^*(a))$ be the solution of the above problem with corresponding multiplier $\mu^*(a)$. Suppose that x^*, y^*, and μ^* are C^1

functions of a and that the nondegenerate constraint qAAlification (NDCQ) holds at $(x^*(a), y^*(a), \mu^*(a))$. Then

$$\mu^*(a) = \frac{d}{da} f(x^*(a), y^*(a))$$

The Lagrangian for this problem is

$$L(x, y, \mu; a) \equiv f(x, y) - \mu(h(x, y) - a)$$

The optimal solutions for $(x^*(a), y^*(a), \mu^*(a))$ must satisfy

$$0 = \frac{\partial L}{\partial x}(x^*(a), y^*(a), \mu^*(a); a) = \frac{\partial f}{\partial x}(x^*(a), y^*(a), \mu^*(a)) - \mu^*(a)\frac{\partial h}{\partial x}(x^*(a), y^*(a), \mu^*(a))$$

$$0 = \frac{\partial L}{\partial y}(x^*(a), y^*(a), \mu^*(a); a) = \frac{\partial f}{\partial y}(x^*(a), y^*(a), \mu^*(a)) - \mu^*(a)\frac{\partial h}{\partial y}(x^*(a), y^*(a), \mu^*(a))$$

$$h(x^*(a), y^*(a)) = a$$

for all a . Since $h(x^*(a), y^*(a)) = a$ it must be that

$$\frac{\partial h}{\partial x}(x^*, y^*)\frac{dx^*}{da}(a) + \frac{\partial h}{\partial y}(x^*, y^*)\frac{dy^*}{da}(a) = 1$$

for every a . Therefore, using the Chain Rule,

$$\begin{aligned}
\frac{d}{da} f(x^*(a), y^*(a)) &= \frac{\partial f}{\partial x}(x^*(a), y^*(a))\frac{dx^*}{da}(a) + \frac{\partial f}{\partial y}(x^*(a), y^*(a))\frac{dy^*}{da}(a) \\
&= \mu^*(a)\frac{\partial h}{\partial x}(x^*(a), y^*(a))\frac{dx^*}{da}(a) + \mu^*(a)\frac{\partial h}{\partial y}(x^*(a), y^*(a), \mu^*(a))\frac{dy^*}{da}(a) \\
&= \mu^*(a)[\frac{\partial h}{\partial x}(x^*(a), y^*(a))\frac{dx^*}{da}(a) + \frac{\partial h}{\partial y}(x^*(a), y^*(a), \mu^*(a))\frac{dy^*}{da}(a)] \\
&= \mu^*(a) \cdot 1
\end{aligned}$$

and $\mu^*(a)$ measures the rate of change of the optimal value of f with respect to the parameter a . It is not hard to extend the above to the setting below.

Let f , $h_1,\ldots,h_m$ be C^1 function on $\mathbf{R}^n$. Let $\mathbf{b}=(b_1,\ldots,b_m),\mathbf{c}=(c_1,\ldots,c_k)$ be exogenous parameters . Consider the problem of maximizing $f(x_1,\ldots,x_n)$ subject to the constraints

$h_1(x_1,\ldots,x_n)=b_1,\ldots h_m(x_{1,}\ldots,x_n)=b_m$

and inequality constraints

$g_1(x_1,\ldots,x_n)?c_1,\ldots g_k(x_{1,}\ldots,x_n)?c_k$

Let $x_1^*,\ldots,x_n^*$ denote the solution of this problem, with corresponding Lagrange multipliers $\mu_1^*(\mathbf{b}),\ldots,\mu_m^*(\mathbf{b}),\lambda_1^*(\mathbf{c}),\ldots\lambda_k^*(\mathbf{c})$. Suppose further that the x_i^* 's are differentiable function of $(b_1,\ldots,b_m,c_1,\ldots,c_k)$, μ_j^* 's and λ_s^* are differentiable function of $(b_1,\ldots,b_m)$ and $(c_1,\ldots,c_k)$, respectively, and NDCQ holds. Then for each $j=1,\ldots m$

$$\mu_j^*(b_1,\ldots b_m)=\frac{\partial}{\partial b_j}f(x_1^*(b_{1,}\ldots b_m,c_1,\ldots c_k),\ldots x_n^*(b_{1,}\ldots b_m,c_1,\ldots c_k))$$

and for each $s=1,\ldots,k$

$$\lambda_s^*(c_1,\ldots c_k)=\frac{\partial}{\partial c_s}f(x_1^*(b_{1,}\ldots b_m,c_1,\ldots c_k),\ldots x_n^*(b_{1,}\ldots b_m,c_1,\ldots c_k))$$

We can specify the objective function $f(\mathbf{x})$ as the profit function of a firm and interpret the a_j 's on the right-hand sides of the constraints as representing the amounts available for inputs in the firm's production process. In this situation,

$$\frac{\partial}{\partial a_j} f(x_1^*(\mathbf{a}),\ldots x_n^*(\mathbf{a}))$$

represents the change in the optimal profit resulting from the availability of one more unit of input *j* and indicates how valuable another unit of input *j* would be to the firm's profits. Alternatively, it tells the maximum amount the firm would be willing to pay to acquire another unit of input *j*. For this reason, $\lambda_j^*(\mathbf{a})$ is called the shadow price of input *j*.

The shadow value of $q_{c,t}^1$ is

$$\lambda_t^{11} q_{c,t}^1 + \lambda_t^{12} q_{c,t}^2 + \lambda_t^{13} x_{t+1}^1 + \lambda_t^{14} z_{t+1}^1$$

and indicates the extent of market power for AA while the shadow value of $q_{c,t}^2$ is

$$\lambda_t^{21} q_{c,t}^1 + \lambda_t^{22} q_{c,t}^2 + \lambda_t^{23} x_{t+1}^2 + \lambda_t^{24} z_{t+1}^2$$

and provides us a similar measure of market power for AA.

The Kalman filter for AA (Firm1) is

$$p_{c,t}^1 + q_{c,t}^1 \frac{\partial p_{c,t}^1}{\partial q_{c,t}^1} - \frac{\partial c^1}{\partial q_{c,t}^1} + \alpha_{c,t}^1 D_c + \beta(\lambda_t^{11} q_{c,t}^1 + \lambda_t^{12} q_{c,t}^2 + \lambda_t^{13} x_{t+1}^1 + \lambda_t^{14} z_{t+1}^1) = 0 \Leftrightarrow$$

$$\left(\frac{\partial c^1}{\partial q_{c,t}^1} - p_{c,t}^1 - q_{c,t}^1 \frac{\partial p_{c,t}^1}{\partial q_{c,t}^1}\right)\beta^{-1} = \alpha_{c,t}^1 \frac{D_c}{\beta} + \lambda_t^{11} q_{c,t}^1 + \lambda_t^{12} q_{c,t}^2 + \lambda_t^{13} x_{t+1}^1 + \lambda_t^{14} z_{t+1}^1 \Leftrightarrow$$

$$Y_t^1 = X_t^{1'} B_t^1 + e_t$$

where

$$Y_t^1 = (\frac{\partial c^1}{\partial q_{c,t}^1} - p_{c,t}^1 - q_{c,t}^1 \frac{\partial p_{c,t}^1}{\partial q_{c,t}^1})\beta^{-1}$$

$$X_t^{1'} = (\frac{D_c}{\beta}, q_{c,t}^1, q_{c,t}^2, x_{t+1}^1, z_{t+1}^1)$$

$$B_t^{1'} = (\alpha_{c,t}^1, \lambda_t^{11}, \lambda_t^{12}, \lambda_t^{13}, \lambda_t^{14})$$

while for UA (Firm2) the Kalman filter is

$$p_{c,t}^2 + q_{c,t}^2 \frac{\partial p_{c,t}^2}{\partial q_{c,t}^2} - \frac{\partial c^2}{\partial q_{c,t}^2} + \alpha_{c,t}^2 D_c + \beta(\lambda_t^{21} q_{c,t}^1 + \lambda_t^{22} q_{c,t}^2 + \lambda_t^{23} x_{t+1}^2 + \lambda_t^{24} z_{t+1}^2) = 0 \Leftrightarrow$$

$$(\frac{\partial c^2}{\partial q_{c,t}^2} - p_{c,t}^2 - q_{c,t}^2 \frac{\partial p_{c,t}^2}{\partial q_{c,t}^2})\beta^{-1} = \alpha_{c,t}^2 \frac{D_c}{\beta} + \lambda_t^{21} q_{c,t}^1 + \lambda_t^{22} q_{c,t}^2 + \lambda_t^{23} x_{t+1}^2 + \lambda_t^{24} z_{t+1}^2 \Leftrightarrow$$

$$Y_t^2 = X_t^{2'} B_t^2 + e_t$$

where

$$Y_t^2 = (\frac{\partial c^2}{\partial q_{c,t}^2} - p_{c,t}^2 - q_{c,t}^2 \frac{\partial p_{c,t}^2}{\partial q_{c,t}^2})\beta^{-1}$$

$$X_t^{2'} = (\frac{D_c}{\beta}, q_{c,t}^1, q_{c,t}^2, x_{t+1}^2, z_{t+1}^2)$$

$$B_t^{2'} = (\alpha_{c,t}^2, \lambda_t^{21}, \lambda_t^{22}, \lambda_t^{23}, \lambda_t^{24})$$

The state equations are not defined. One possibility is a simple auto-regression for both carriers such as

$$B_t^1 = B_{t-1}^1 + \upsilon_t^1$$

$$B_t^2 = B_{t-1}^2 + \upsilon_t^2$$

while another possibility is to include the strictly exogenous variables.

Second, we can use the same approach as above, but assume that the coefficients on the x and z terms are constants (no t subscripts): λ^3 and λ^4. Now we only have to determine two terms using Kalman filters. Third, we can reduce the number of λ terms. For AA (Firm1) we can write

$$p_{c,t}^1 + q_{c,t}^1 \frac{\partial p_{c,t}^1}{\partial q_{c,t}^1} - \frac{\partial c^1}{\partial q_{c,t}^1} + \alpha_{c,t}^1 D_c + \beta\left[\lambda_t^{11} q_{c,t}^1 + \lambda_t^{12} q_{c,t}^2 + \lambda_t^{13} f(x_{t+1}^1, z_{t+1}^1)\right] = 0$$

and for AA (Firm2) we can write

$$p_{c,t}^2 + q_{c,t}^2 \frac{\partial p_{c,t}^2}{\partial q_{c,t}^2} - \frac{\partial c^2}{\partial q_{c,t}^2} + \alpha_{c,t}^2 D_c + \beta\left[\lambda_t^{21} q_{c,t}^1 + \lambda_t^{22} q_{c,t}^2 + \lambda_t^{23} f(x_{t+1}^2, z_{t+1}^2)\right] = 0$$

We now have three λ terms that we need to determine using Kalman filters. We could allow λ_t^{ij} to be determined by a Kalman filter that depends on x and not on z. The state equations are then

$$\lambda_t^{11} = \rho_0^{11} + \rho_1^{11}\lambda_{t-1}^{11} + \rho_2^{11} x_{t+1}^1 + \rho_3^{11} q_t^1 + \rho_4^{11} q_t^2 + \varepsilon_t$$

$$\lambda_t^{12} = \rho_0^{12} + \rho_1^{12}\lambda_{t-1}^{12} + \rho_2^{12} x_{t+1}^1 + \rho_3^{12} q_t^1 + \rho_4^{12} q_t^2 + \varepsilon_t$$

$$\lambda_t^{21} = \rho_0^{21} + \rho_1^{21}\lambda_{t-1}^{21} + \rho_2^{21} x_{t+1}^2 + \rho_3^{21} q_t^1 + \rho_4^{21} q_t^2 + \varepsilon_t$$

$$\lambda_t^{22} = \rho_0^{22} + \rho_1^{22}\lambda_{t-1}^{22} + \rho_2^{22} x_{t+1}^2 + \rho_3^{22} q_t^1 + \rho_4^{22} q_t^2 + \varepsilon_t$$

Providing that f is linear in z and providing that we know β, the first order condition is linear in parameters and can be estimated using the linear Kalman Filter.

The estimation results reported below are based on the first method discussed above. The state equation is defined as a simple auto-regression. Since we estimate the model by each city pair, D_c is dropped. We include D_c when we compare AA with AA by multiple city pairs.

We illustrate in detail how we derive the estimated results of AA between city-pair Chicago (ORD) and San Diego (SAN). Estimates for other city-pairs are straightforward extensions. The first-order condition for AA (Firm 1) between city pair Chicago (ORD) and San Diego (SAN) is:

$$p_t^1 + q_t^1 \frac{\partial p_t^1}{\partial q_t^1} - \frac{\partial c^1}{\partial q_t^1} + \alpha + \beta(\lambda_t^{11} q_t^1 + \lambda_t^{12} q_t^2 + \lambda_t^{13} x_{t+1}^1 + \lambda_t^{14} z_{t+1}^1) = 0 \Leftrightarrow$$

$$(\frac{\partial c^1}{\partial q_t^1} - p_t^1 - q_t^1 \frac{\partial p_t^1}{\partial q_t^1})\beta^{-1} = \alpha\beta^{-1} + \lambda_t^{11} q_{c,t}^1 + \lambda_t^{12} q_{c,t}^2 + \lambda_t^{13} x_{t+1}^1 + \lambda_t^{14} z_{t+1}^1 \Leftrightarrow$$

$$Y_t^1 = X_t^{1'} B_t^1 + e_t$$

where

$$Y_t^1 = (\frac{\partial c^1}{\partial q_t^1} - p_t^1 - q_t^1 \frac{\partial p_t^1}{\partial q_t^1})\beta^{-1}$$

$$X_t^{1'} = (\frac{1}{\beta}, q_t^1, q_t^2, x_{t+1}^1, z_{t+1}^1)$$

$$B_t^{1'} = (\alpha, \lambda_t^{11}, \lambda_t^{12}, \lambda_t^{13}, \lambda_t^{14})$$

We assume a simple demand function given by

$$P = A - Q = A - q_1 - q_2$$

where A is a constant.

We use estimates of the average cost when route is defined by city pair **(avcstcty)**, average price when the route is a city pair **(avgprcty)**, and the number of passengers on a route **(rtpass)** from Perloff et al. (2003). Our results are based on an assumed discount factor β of 0.9, but a value of 0.95 was also examined and the results were qualitatively similar. This yields the following equation

$$Y_t^1 = \left(\frac{\partial c^1}{\partial q_t^1} - p_t^1 - q_t^1 \frac{\partial p_t^1}{\partial q_t^1}\right)\beta^{-1} = (avctscty - avgprcty + rtpass) / 0.9$$

We use national per capita income **(pcinc)** as an economy-wide exogenous variable X_t and Herfindahl index for city pair **(herfcty)** as an city-pair specific exogenous variable Z_t which appears to be the best city-pair specific exogenous variable we could find in the available data. In this context then

$$X_t^{1'} = \left(\frac{1}{\beta}, q_t^1, q_t^2, x_{t+1}^1, z_{t+1}^1\right) = \left(\frac{1}{0.9}, rtpass_t^1, rtpass_t^2, pcinc_{t+1}^1, h\,\mathrm{erf}\,cty_{t+1}^1\right)$$

$$B_t^{1'} = (\alpha, \lambda_t^{11}, q_t^{12}, \lambda_t^{13}, \lambda_t^{14})$$

We look at a set of city pairs in which American and United are dominant firms and assume that the competitive environment in which the firms compete is Markovian. The source of data was the Databank 1A (DB1A) of the Department of Transportation (DOT). DB1A, collected quarterly, provides a 10% sample of all tickets sold for travel on US airlines. The level of observation in this dataset is the airline-route-routing-quarter. Each observation contains information on the carrier flown, the route traveled (the origin and destination airports), the routing (direct service or connecting service through a particular airport), the quarter of travel, the type of ticket (one-way, roundtrip or open-jaw), the dollar fare paid and the distance of the trip. The data also contain a variable indicating the point of purchase of the ticket, which allows departing and returning legs of roundtrip tickets to be distinguished. Unfortunately, the data do not contain any information on the details of the ticket, such as whether the ticket required a Saturday night stay-over or whether the ticket was purchased 7 or 14 days in advance. The data also do not identify the date or time of travel (only the quarter), so observations cannot be matched to particular days of the week or specific flight numbers. The data are taken directly from airline ticket stubs and, along with the total ticket price; the data contains such information as the carrier, origin, destination, and class for all trip segments. The data are by airline and by quarter from 1979I-1988IV. In many cases our choice of study period is interesting because many fare innovations and service quality changes occurs during this time period following the deregulation of the industry in 1978. The airlines we discuss in this chapter are American and United. Economy-wide exogenous variables and city pair specific variables are important controls in the model and consist of; the existence of a frequent flier program, strikes, alliances, the Gulf War, the air controller's strike under the Reagan Administration, mergers, price of jet fuel and national taxes on airlines. The city-pair specific exogenous variables consist of city pair and region dummies, international airport dummies, delays, entry and exit, share of minor carriers on the route, unemployment rate for each city, percent change in state GDP and relative or actual marginal cost.

These variables have been examined in a somewhat different reduced form market power setting in Weiher, Sickles and Perloff (2003) and in the context of constructing a hedonic airline price index (Good, Sickles and Weiher, 2007).

Good, Sickles and Weiher (2007) estimates a quality-adjusted price index for airline fares using a hedonic price regression which includes quality characteristics as well as time dummies based on DOT origin and destination (O&D). When the products under consideration are simple homogeneous commodities, CPI is best computed. But CPI does not describe the air transport industry, because air travel takes place between different origins and destinations over alternative paths and with differing levels of service. Good, Sickles and Weiher (2007) consider three hedonic characteristics of the airlines. Network configuration: the indirectness of routing, change of planes, and the number of airlines used to complete the trip.

Using the DB1A, Good, Sickles and Weiher (2007) identify the origin and the ultimate destination as indicated by a trip break. Approximately 20 percent of trips involve one way tickets (no trip breaks), 65 percent are one way (one trip break at the destination), and the remaining 5 percent involve open jaw or multi-break tickets. The changing pattern of these tickets is described in Figure 1[2]. For each trip type, we identify the complexity of the trip from the DB1A at the ticket level. The travel itinerary allows us to measure the number of segments (changes of planes with the same carrier) required in the itinerary, the number of airlines that were used to provide service, and the number of changes required to a different airline (interlines). For each of these variables the higher the variable is, the lower the quality of service. Figure 2 displays the patterns of one way trips over the sample period while the patterns of round trip itineraries are shown in Figure 3. Their data suggest that there has been some improvement in the quality of service between 1978I-1992IV. If ignored in the computation of price indices these service quality improvements would inflate the rate of growth in prices.

Good, Sickles and Weiher (2007) believes the more departures that occur (higher flight frequency), the more likely that the time of departure will match the most desired time for the passenger, indicating a higher level of service. Figure 4 displays the pattern of change in departures for different sizes of airports. There was a clear shift from very small to larger cities. From the airline's perspective the shift was economical. However, from the passenger's perspective, offering service to small communities was desirable since it reduced travel time. For Good, Sickles and Weiher (2007)'s study, Departures from small communities as an indication of high service quality. Good, Sickles and Weiher (2007)

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2 Figure1 to Figure 7 are cited from Good, Sickles and Weiher (2007)

use hedonic characteristics to measure passenger amenity: food, and class of service. Figure 5 indicates that there has been a gradual increase in food expenditures per passenger. Even when one controls for inflation in food prices, they still find 25 percent increase in real expenditures per passenger during the sample period, which would indicate about 3 percent of the price of travel, on average, could be attributed to food expense.

Figure 1. Fraction of One Way Tickets Sold

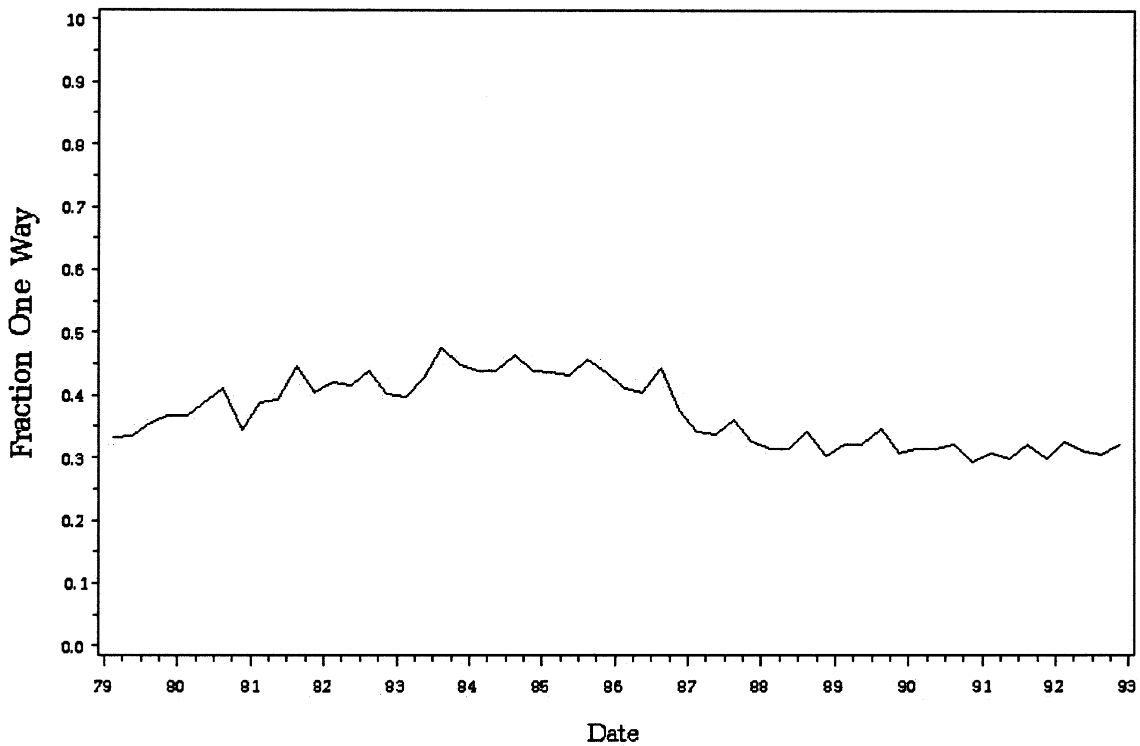


Figure 2. Patterns of One Way Itineraries

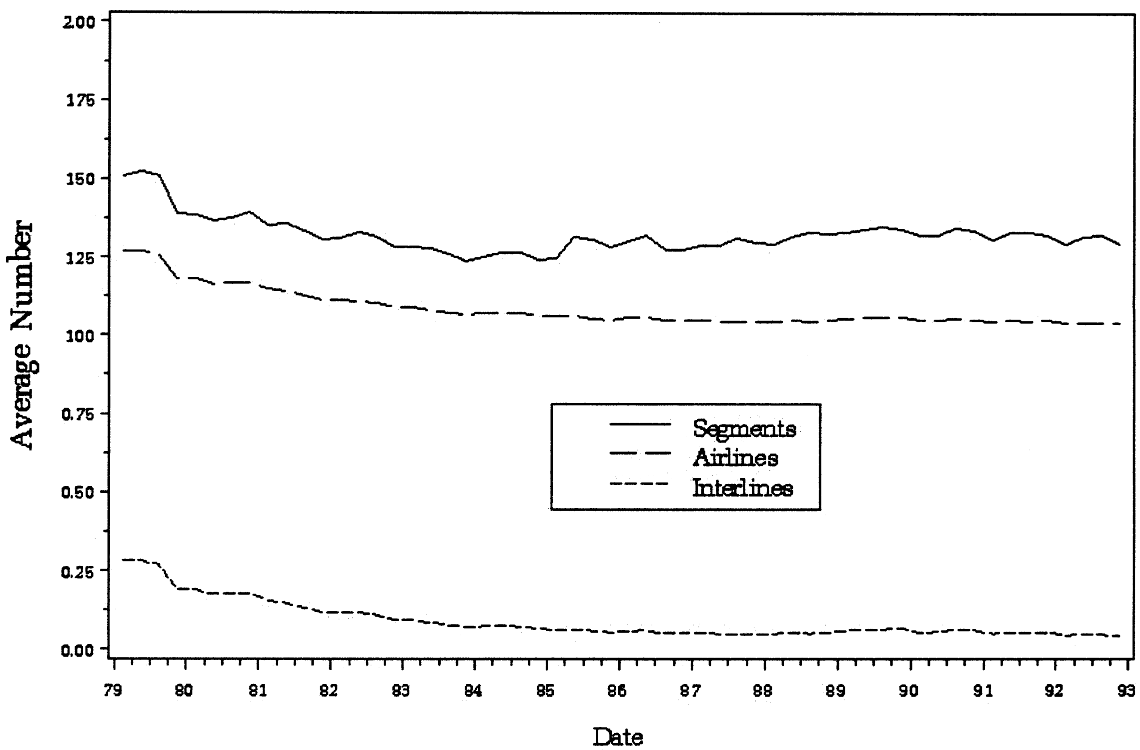


Figure 3. Patterns of Round Trip Itineraries

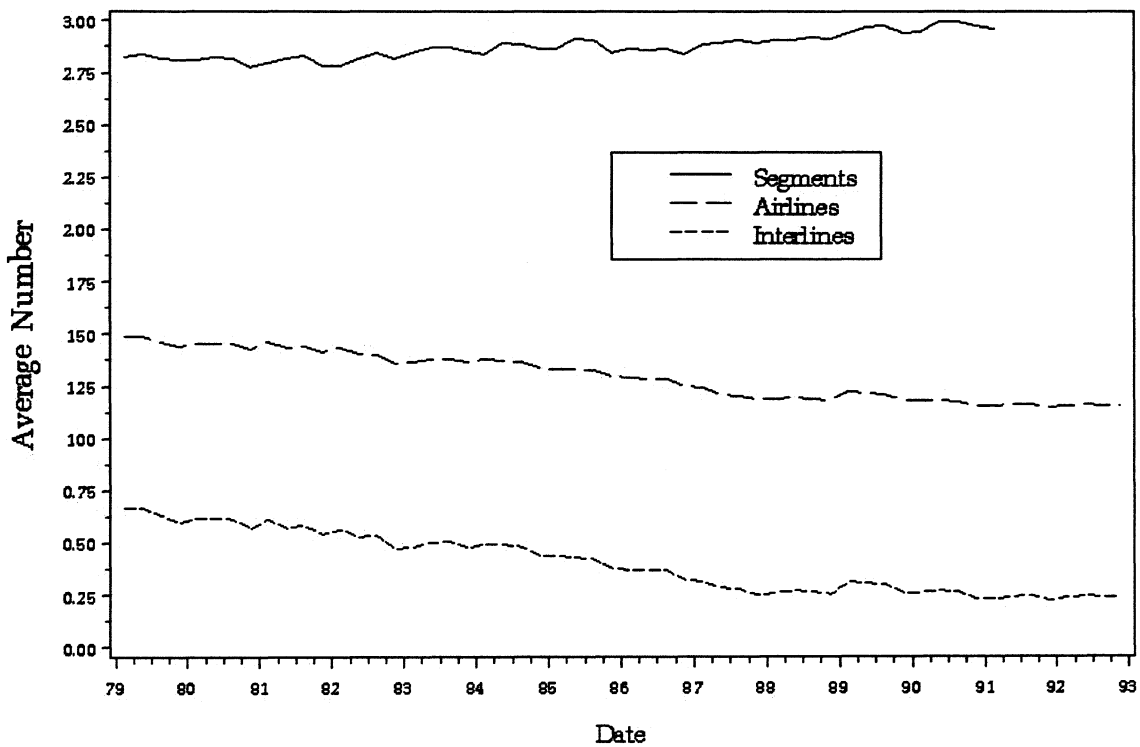


Figure 4. Number of Departures by Airport Size

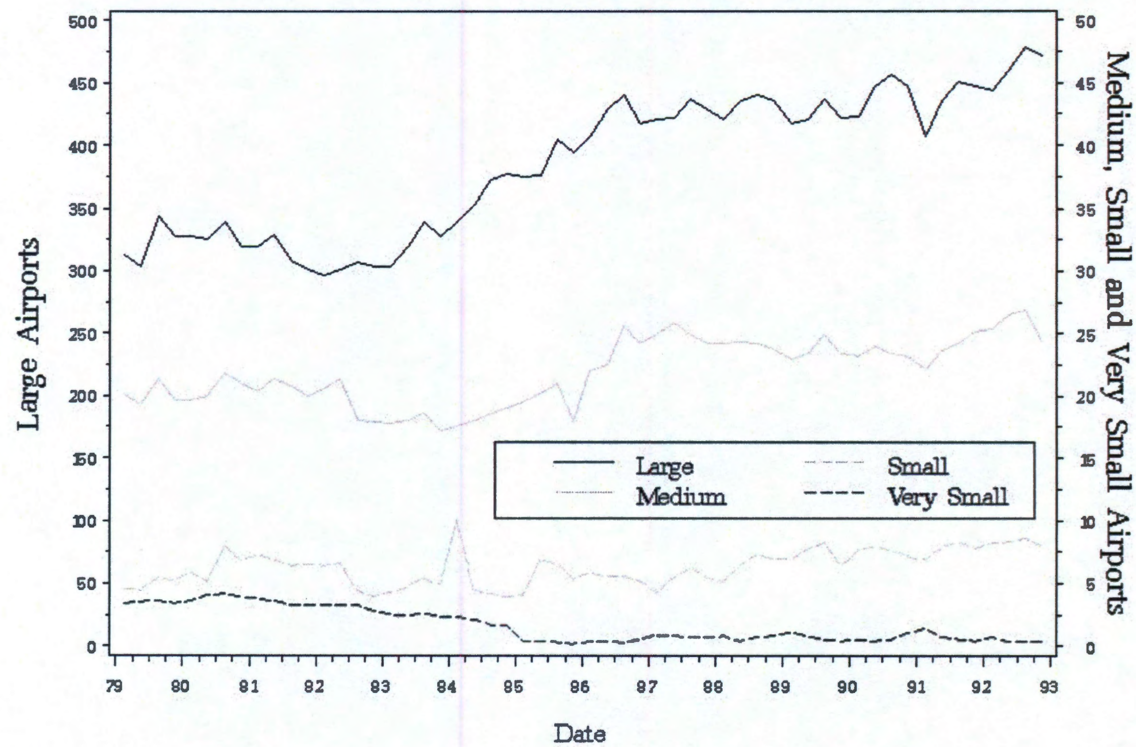


Figure 5. Airline Food Expenditures

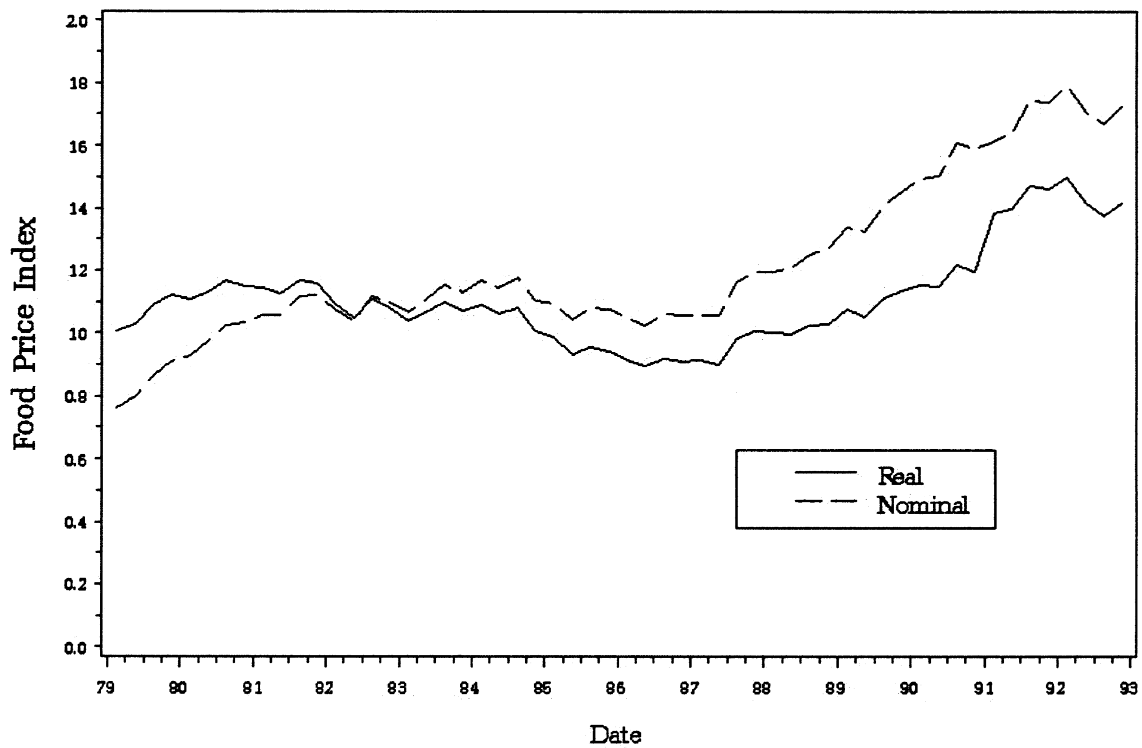


Figure 6 shows the fraction of all tickets which were discounted coach tickets for one way and round trip travel during the sample period. The data show steady increase in both one way and round trip tickets that are discounted coach. For round trip tickets, only 30 percent of tickets were discounted coach in 1979I, increased to nearly 90 percent by 1992 IV. Frequent flyer miles were introduced in the mid 1980s by then CEO Robert Crandall of American Airlines. The purpose of this program was to increase customer loyalty by offering them free travel at a later date. The pattern of these tickets can be seen in Figure7 for one way and round trip travel. For both round trip and one way travel there is a spike in 1987 associated with the introduction of these tickets to about 10 percent for both one way and round trip travel. Good, Sickles and Weiher (2007) believes that several route characteristics clearly affect the price of travel. These characteristics include the distance between the origin and destination, mean temperature difference in an attempt to capture vacation travel in the winter months, variables which attempt to capture the demand for business travel such as the number of white collar jobs in an area. In their model, they assume that these factors are either very slow to change or that they are strongly correlated with other factors in their model (for example, white collar jobs are likely correlated with per capita income). They capture these slowly moving factors with fixed route specific effects which describe the origin-destination pair. They also considered the use of other factors. These included safety, compliant data, and control for local demand characteristics such as growth of local GDP and employment rates at origin and destination.

Figure 6. Fraction of Discounted Coach and First Class Tickets

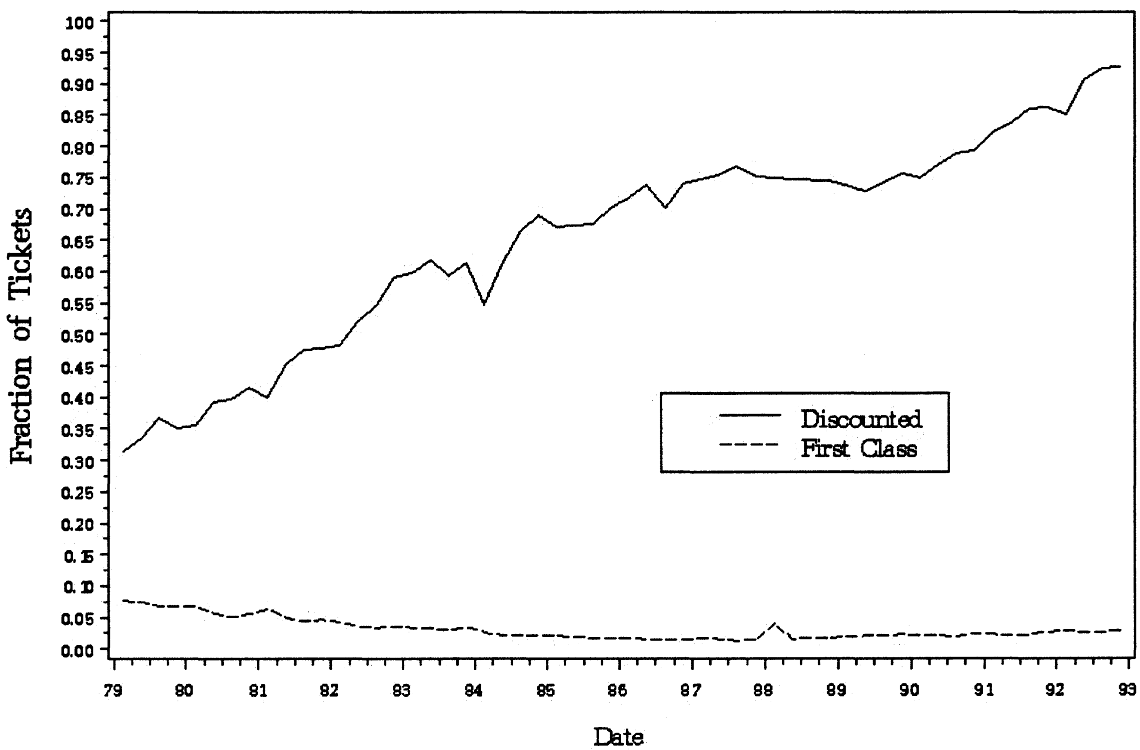
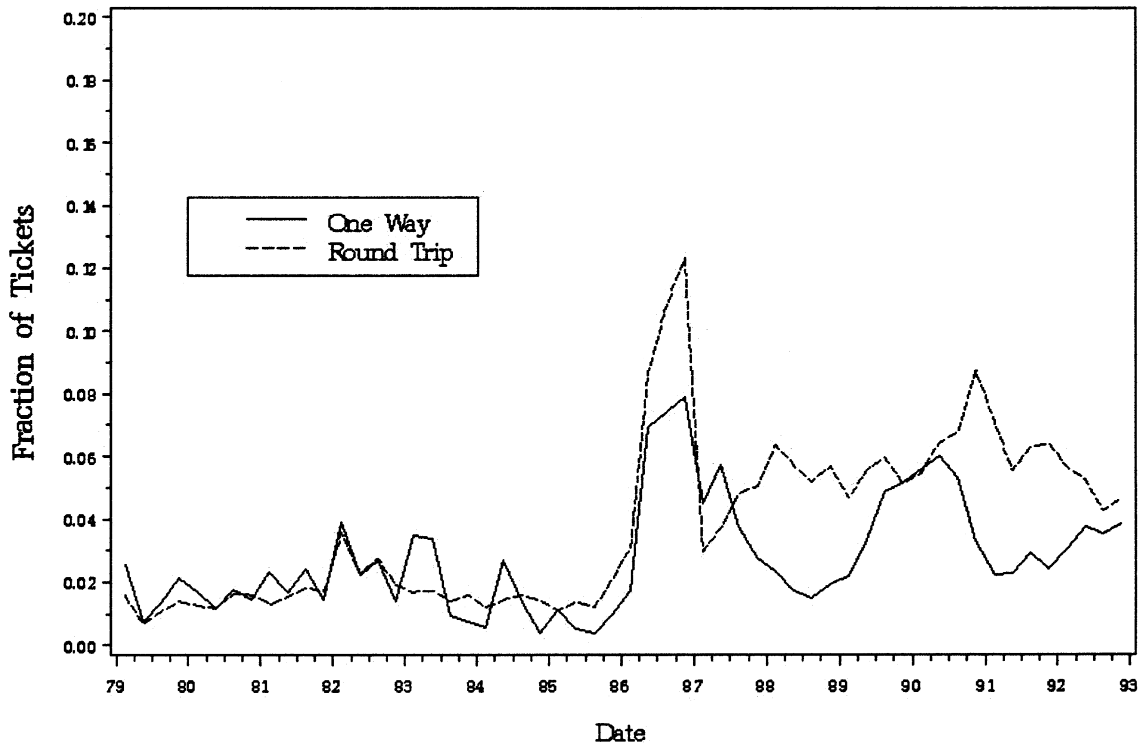


Figure 7. Fraction of One Way and Round Trip Zero Coupon Tickets



Good, Sickles and Weiher (2007) simulates Bureau of Labor Statistics (BLS) current methodology over the study period, without the advantage of using their data. And then compare these results to price indices which allow for increased substitutability in market baskets by using sales information and adjust the price index by holding attributes of service quality fixed. The replicated indices match very well with the actual index reported by the BLS. Since one way and round trip tickets in terms of both the passenger and the airline have key differences. Consequently, they develop separate demand models for one way and round trips and discuss these results before combining them in an overall aril travel demand model. They first estimate a base model that does not include any aspects of service quality:

$$\ln P_{ijt} = \alpha_j + \beta_t D_t + \varepsilon_{ijt}$$

For ticket i on route j at time t. β_t is the coefficient on a dummy time variable where the reference category is time period 1979I. Omitted service quality characteristics may be correlated with fixed time and/or route effects, therefore, the OLS estimates of $\alpha_j's$ and $\beta_j's$ may be biased and inconsistent. They use predicted price ratio from 1979I to time t. Their hedonic model includes the effects of restriction and service quality

$$\ln P_{ijt} = \alpha_j + \beta_t D_t + \sum_k r_t X_{kijt} + \varepsilon_{ijt}$$

Where the X_{kijt} are the k measures of service quality and ticket discounting for ticket i on route j. In this model they control for the expenditures on food, the number of departures, the number of segments (more segments indicating a more circuitous trip and required changes of planes), interlining (the requirement that passengers also change airlines when they change planes), the class of service (dummy indicating first class) and whether or not the ticket has fare restrictions. The corresponding quantity index of tickets correspond to the total price of a ticket divided by the imputed quality adjusted price index for a flight on a particular route for a particular airline at a point in time.

DOT's airline data set includes four inputs: labor, energy, flight capital and a residual category, materials, that includes supplies, outside services, and non-flight capital. The data set includes two outputs: scheduled and non-scheduled revenue passenger-miles. Weiher, Sickles and Perloff (2003) constructed quantity and price data using the multilateral Tornqvist-Theil index number procedure. They aggregate 93 separate labor accounts into five major employment classes (flight deck crews, flight attendants, mechanics, passenger/cargo/aircraft handlers, and other personnel). Energy input was constructed by combining information on aircraft fuel gallons used with fuel expense data per period. They aggregated 69 separate expenditure accounts into 12 broad classes of materials or other input that did not fit into the labor, energy, or flight capital categories. They constructed the average number of aircraft in service for each quarter by dividing the total number of aircraft days for all aircraft types by the number of days in the quarter. The measure of flight capital was adjusted by the average equipment size. Weiher, Sickles and Perloff (2003) calculated the price per unit (passenger-mile or ton-mile) of the relevant service by dividing the revenue generated in the category by the physical amount of output in that category. Passenger load factor is calculated by dividing revenue passenger-miles by available seat-mailes. Average stage length is found by dividing total revenue aircraft miles flown by total revenue aircraft departure.

Weiher, Sickles and Perloff (2003) assumes that the individual cost functions are Cobb_Douglas

$$\ln Cost =$$
$$\beta_1 Revenue\ Passenger\ Miles +$$
$$\beta_2 \ln Enplanements + \beta_3 \ln Cargo\ Ton\ Miles + \beta_4 \ln Cities + \beta_5 \ln Load\ Factor +$$
$$\beta_6 \ln Average\ Stage\ Length + \beta_7 \ln Labor\ Price + \beta_8 Fuel\ Price + \beta_9 Materials\ Price +$$
$$\beta_{10} \ln Captial\ Price + \sum_{i=1}^{number\ of\ arilines} \delta_i Airline_i$$

Revenue Passenger Miles are the sum of the miles traveled by paying passengers. Enplanements are the sum of passengers on all flights. Cargo Ton Miles are the number of cargo ton miles per flight. Caves, Christensen, and Tretheway (1984) suggest that network size is an important reason why airline costs differ. As the number of cities increase, holding number of passenger miles constant, the density of traffic on the carriers' network tends to decrease. Load Factor allows us to consider the effects of changes in revenue passenger miles, while holding the number of available seat miles constant. One would expect that increasing revenue passenger miles while holding available seat miles constant would have a very low cost since it involves simply filling up an otherwise empty seat. For a cross-sectional, time series model, Weiher, Sickles and Perloff (2003) estimates the scale elasticity is 1.018, which is not statistically different from 1 at conventional significance level. Using these estimates, they calculate various carrier and time-specific marginal costs for the passenger's flight:

$$Terminal\ costs = MC_{Enplanements}$$

$$Per\ Mile\ Cost = MC_{Revenue\ Passenger\ Miles}$$

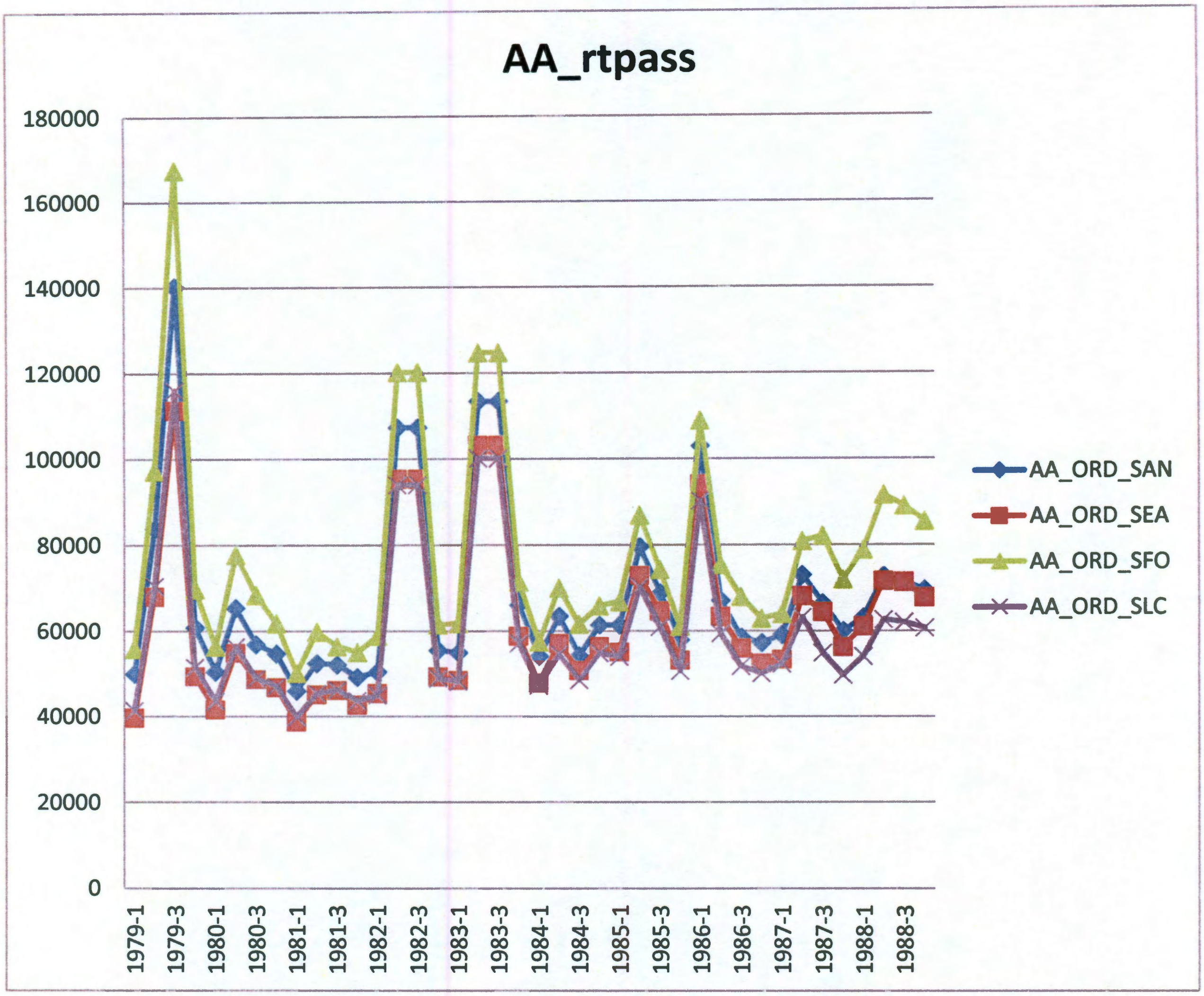
$$Total\ Segment\ Cost = MC_{Enplanements} + MC_{Revenue\ Passenger\ Miles} \times Miles\ Flown$$

After estimating marginal costs, Weiher, Sickles and Perloff (2003) calculate the Total Itinerary Cost as

$$\sum_{i}^{number\ of\ segments} MC_{Enplanement}^{i,carrier_i} + MC_{Revenue\ Passneger\ Miles}^{i,carrier_i} \times Distance_i$$

Where i indexes segments and $carrier_i$ is the carrier for segment i.

These variables have been examined in this chapter is in a somewhat different reduced form market power setting in Weiher, Sickles, and Perloff (2003) and in the context of constructing a hedonic airline price index (Good, Sickles and Weiher 2007). We choose two airlines, American (AA) and United (UA) data from Databank 1A (DB1A) Department of Transportation (DOT) data during period 1979I -1988IV. Some previous studies focus on trips between origin and destination airports. However, doing so neglects the competition that airlines face from carriers that fly from different airports within the same city. Therefore, we use City-Pairs instead of Airport-Pairs. Among all City-Pairs that UA and AA are top two dominant carriers, we choose four City-Pairs to analyze. They are Chicago-San Diego, Chicago-Seattle, Chicago-San Francisco and Chicago-Salt Lake City. We use estimates of the average cost when route is defined by city pair **(avcstcty)**, average price when the route is a city pair **(avgprcty)**, and the number of passengers on a route **(rtpass)** from Perloff et al. (2003). Our results are based on an assumed discount factor β of 0.9, but a value of 0.95 was also examined and the results were qualitatively similar. In addition, we use national per capita income **(pcinc)** as an economy-wide exogenous variable X_t and Herfindahl index for city pair **(herfcty)** as an city-pair specific exogenous variable Z_t which appears to be the best city-pair specific exogenous variable we could find in the available data.



AA_rtpass
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160000
140000
120000
100000
80000
60000
40000
20000
0
1979-1
1979-3
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
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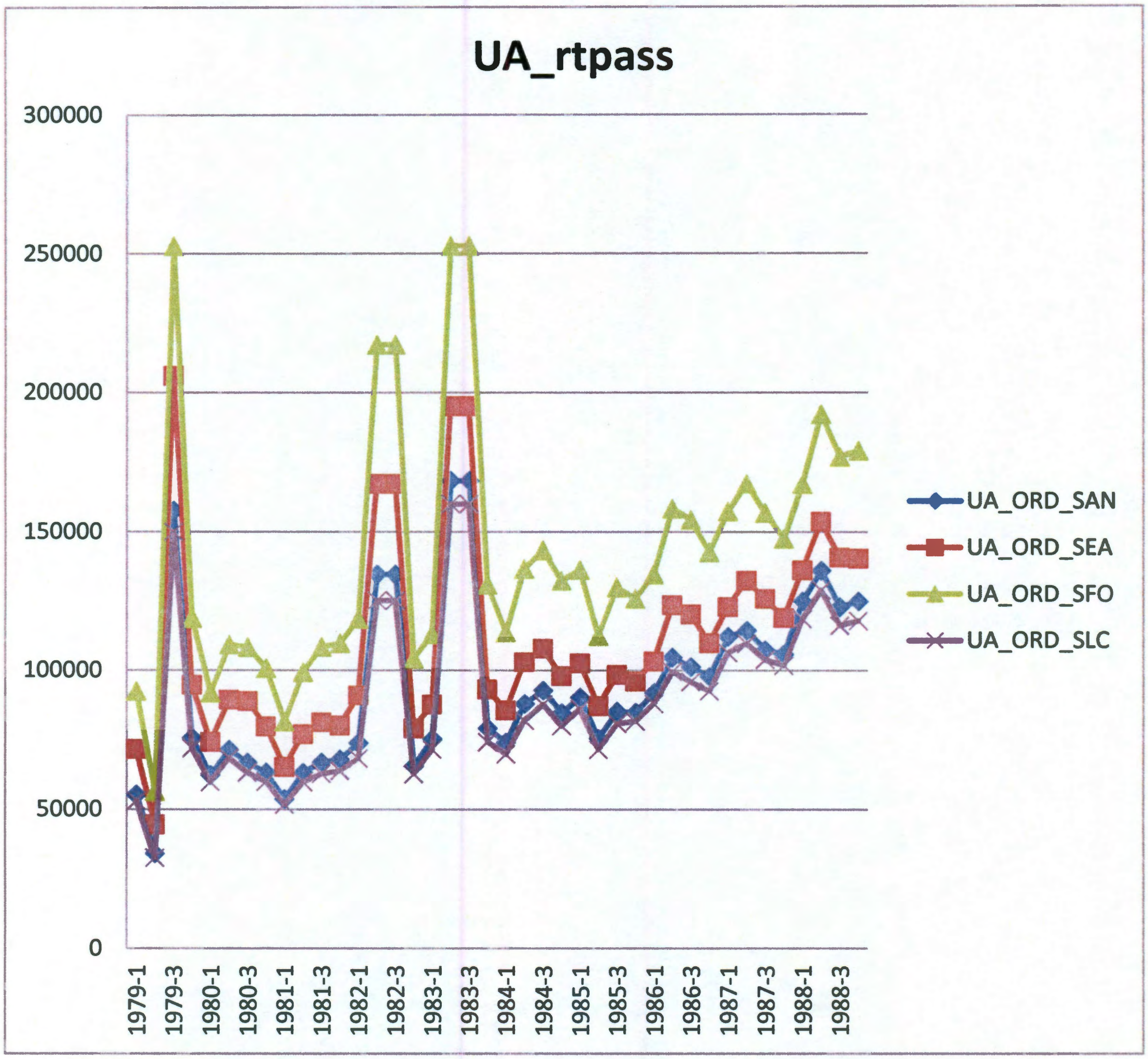
1987-3
1988-1
1988-3
AA_ORD_SAN
AA_ORD_SEA
AA_ORD_SFO
AA_ORD_SLC



UA_rtpass
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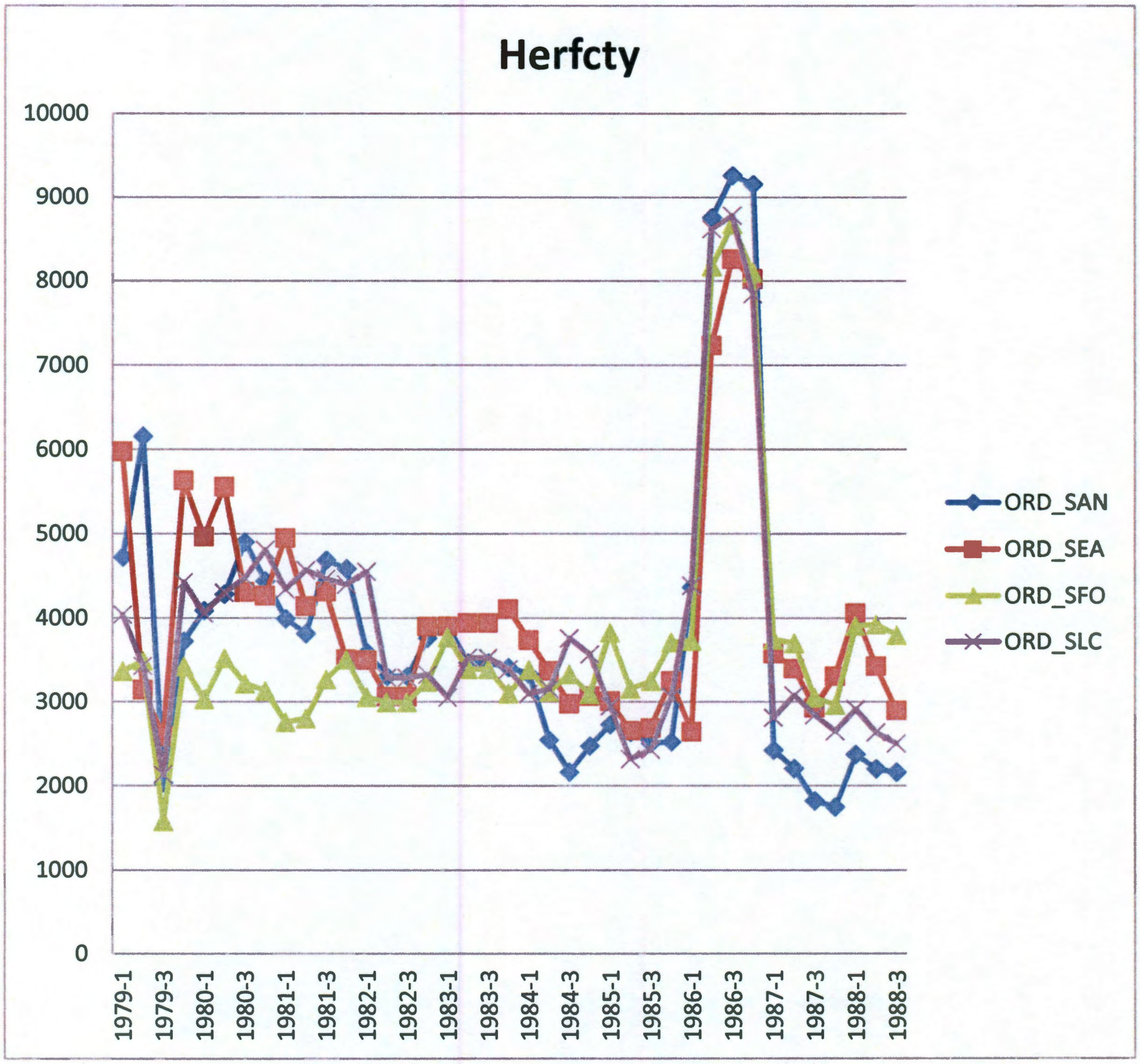
250000
200000
150000
100000
50000
0
1979-1
1979-3
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
1987-1
1987-3
1988-1
1988-3
UA_ORD_SAN
UA_ORD_SEA
UA_ORD_SFO
UA_ORD_SLC


Herfcty
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1979-1
1979-3
1980-1
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1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
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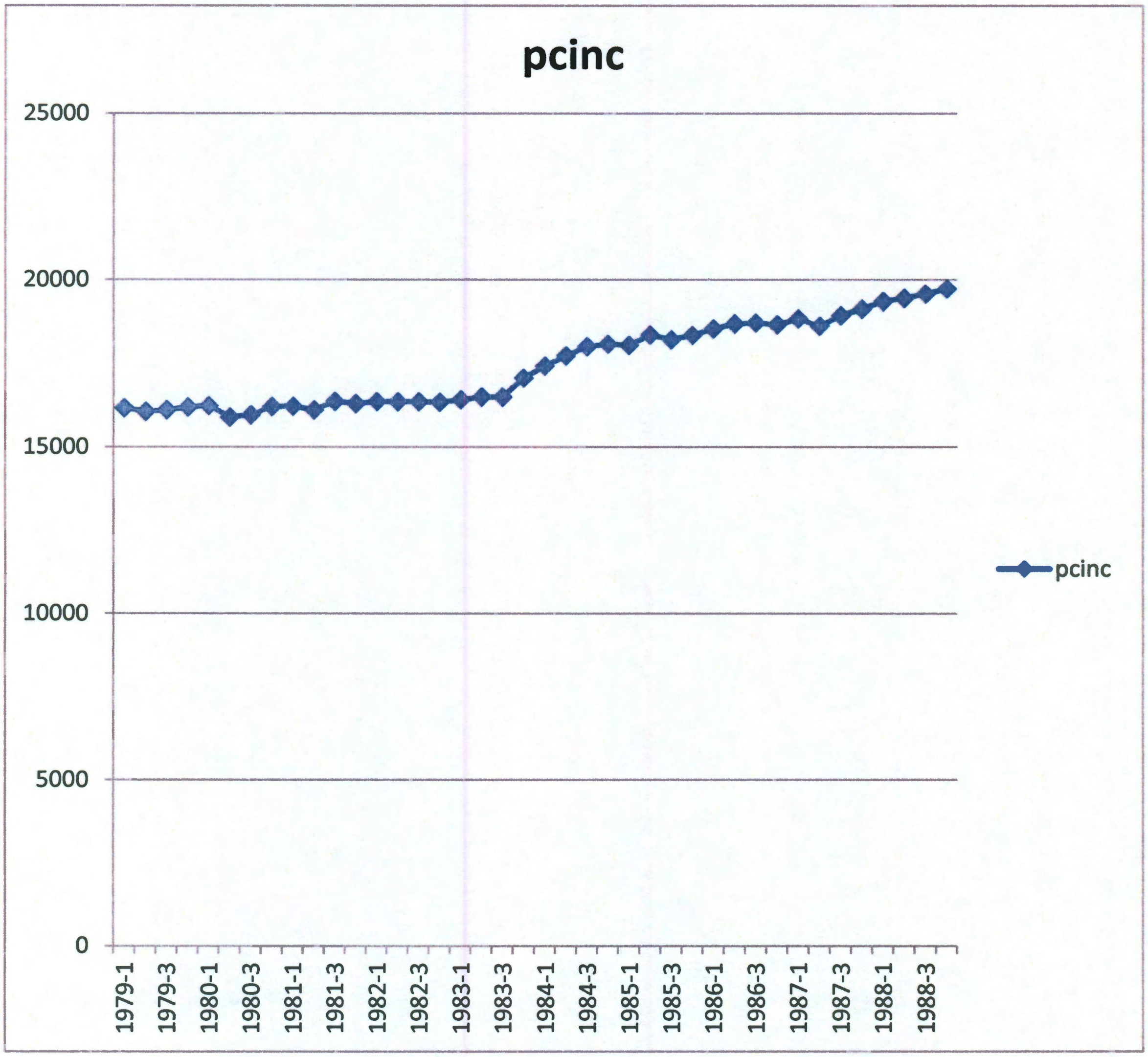
1988-3
ORD_SAN
ORD_SEA
ORD_SFO
ORD_SLC


pcinc
25000
20000
15000
10000
5000
0
1979-1
1979-3
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
1987-1
1987-3
1988-1
1988-3
pcinc

1.5. Empirical Results

Estimation results are reported in Tables 1 and 2. The cities are Chicago (ORD), Salt Lake City (SLC), San Diego (SAN), San Francisco (SFO), and Seattle (SEA). Numerical issues with our algorithm prevented us from estimating accurately the standard errors for several of the variables. Those entries are left blank in the Tables

Table 1 AA

City Pair	ORD-SAN	ORD-SEA	ORD-SFO	ORD-SLC
λ^{11} Estimates	0.64976652	0.34198363	0.35672006	0.00000596
λ^{11} SE	0.09058998	0.08449455	0.09268303	0.23502357
λ^{12} Estimates	0.00000552	0.16309741	0.16265314	0.44189663
λ^{12} SE	**	0.09752401	0.11300235	0.13558679
λ^{13} Estimates	0.13236929	0.15559350	0.14523205	0.24318685
λ^{13} SE	0.08278507	0.07760735	0.07974509	0.19779975
λ^{14} Estimates	0.00001244	0.00000927	0.00000201	0.00000029
λ^{14} SE	0.05990846	0.04294906	0.04234850	0.07371905

Table 2 UA

City Pair	ORD-SAN	ORD-SEA	ORD-SFO	ORD-SLC
λ^{21} Estimates	0.69631873	0.00034146	0.00017537	0.00000281
λ^{21} SE	0.10723028	0.35834513	**	**
λ^{22} Estimates	0.00001757	0.30445244	0.29264571	0.45626616
λ^{22} SE	0.19210776	0.11489267	0.09255699	0.12926968
λ^{23} Estimates	0.18620294	0.35685817	0.38122657	0.33791960
λ^{23} SE	0.11633113	0.10459605	0.08599149	0.04786982
λ^{24} Estimates	0.00000065	0.00000525	0.00000102	0.00001359
λ^{24} SE	0.1357732	0.24650047	0.032894	**

Comparing λ^{13} with λ^{23} in Tables 1 and 2, AA appears to be more significantly influenced by the economy-wide exogenous variables than UA since $\lambda^{13} > \lambda^{23}$. Neither AA nor UA is significantly influenced by the city-pair specific variances.

The shadow value of $q_{c,t}^{1}$ is $\lambda_t^{11} q_{c,t}^{1} + \lambda_t^{12} q_{c,t}^{2} + \lambda_t^{13} x_{t+1}^{1} + \lambda_t^{14} z_{t+1}^{1}$ and indicates the extent of AA's market power while $\lambda_t^{21} q_{c,t}^{1} + \lambda_t^{22} q_{c,t}^{2} + \lambda_t^{23} x_{t+1}^{2} + \lambda_t^{24} z_{t+1}^{2}$ is the shadow value of $q_{c,t}^{2}$ and indicates the market power of UA. Based on results from Table 1 and Table 2, we can calculate the market power of AA and UA, at sample mean values of the variables. These estimates of $q_{c,t}^{1}$ $q_{c,t}^{2}$ are in Table 3.

Table 3

City Pair	ORD-SAN	ORD-SEA	ORD-SFO	ORD-SLC
AA	48155.47814	42739.03961	44788.23266	44267.45226
UA	69711.50634	25440.61308	30158.55228	33775.10931

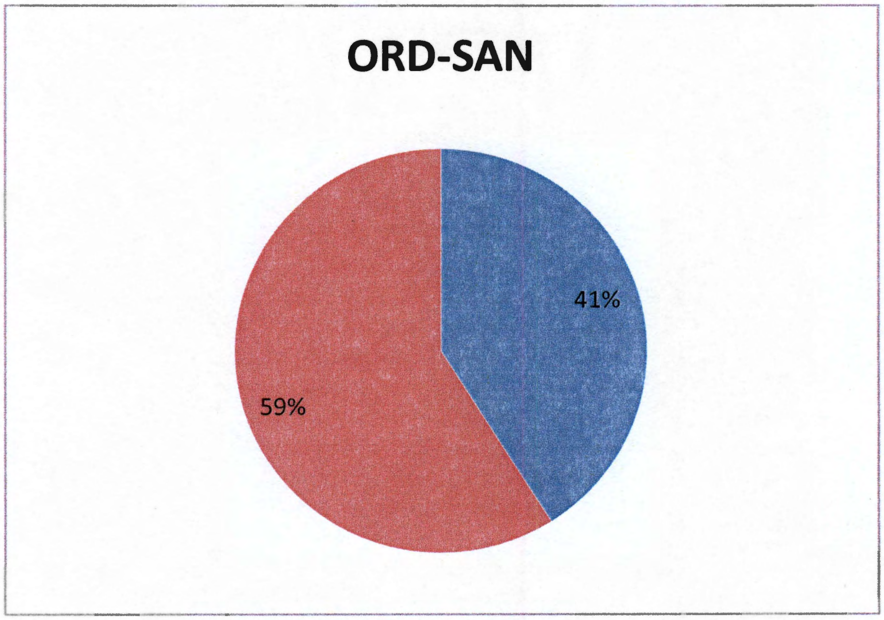
Translating these estimates into market power shares of AA and UA in four city pairs is demonstrated in Table 4.

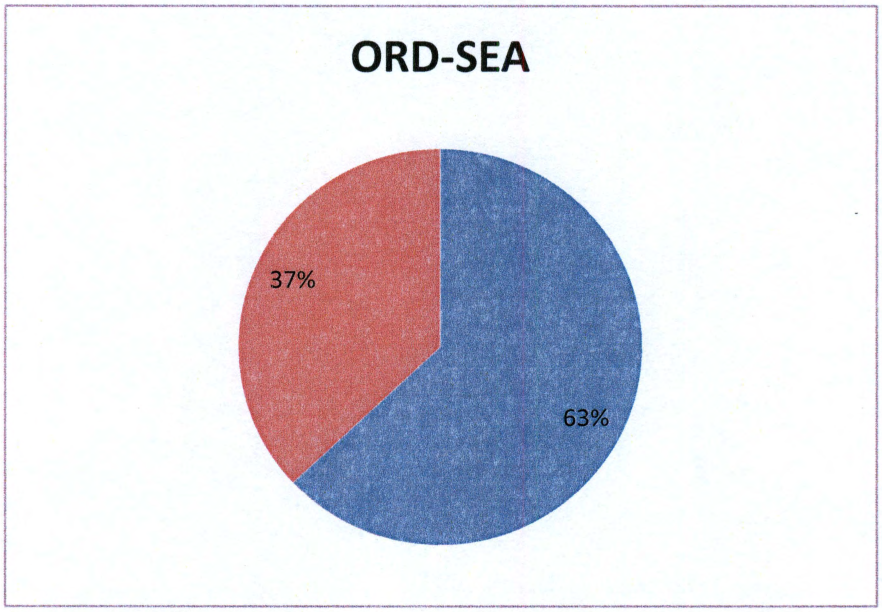
$$Market\ Power_c^1\% = \frac{q_c^2}{q_c^1 + q_c^2}$$

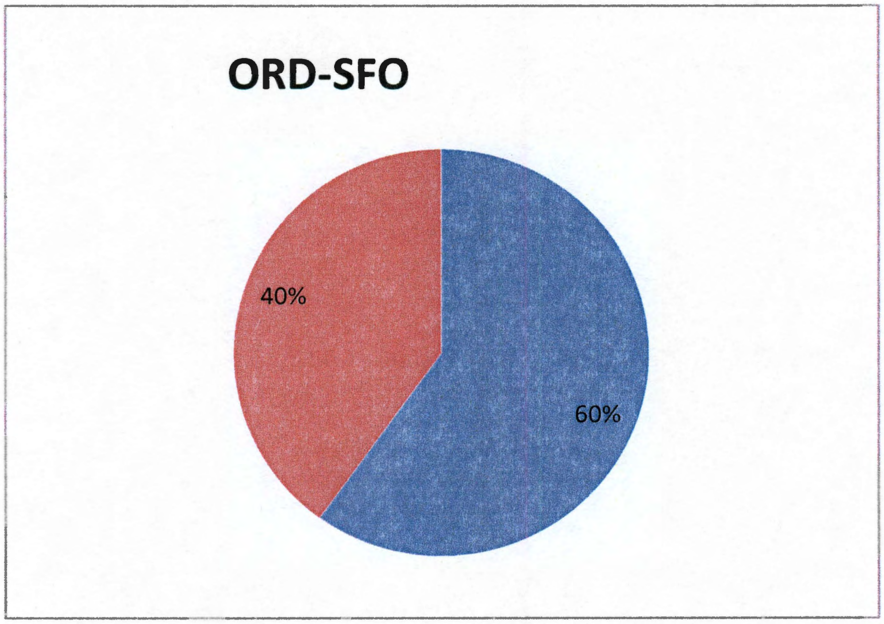
$$Marekt\ Power_c^2\% = \frac{q_c^1}{q_c^1 + q_c^2}$$

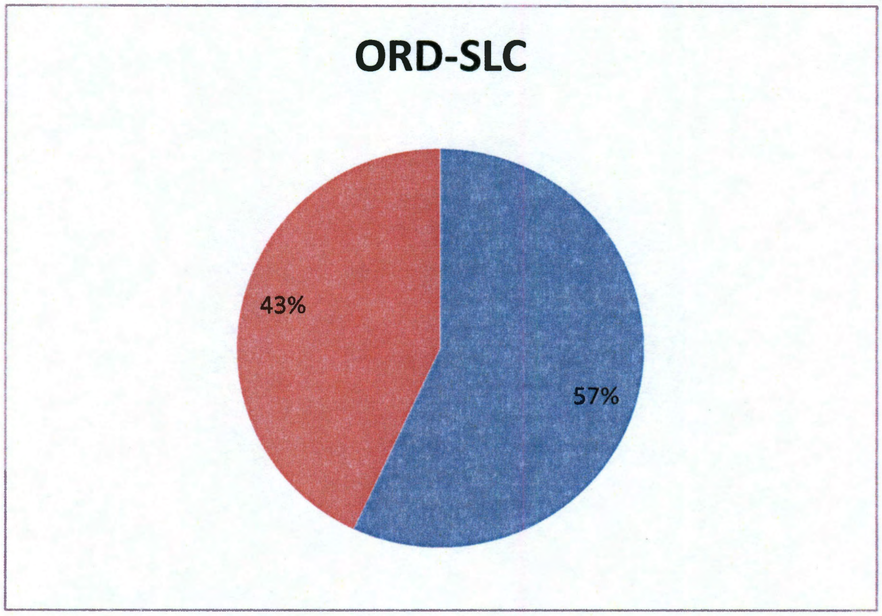
Table 4 Market Power Share of AA and UA in city pairs

City Pair	ORD-SAN	ORD-SEA	ORD-SFO	ORD-SLC
UA	41%	63%	60%	57%
AA	59%	37%	40%	43%


ORD-SAN
41%
59%


ORD-SEA
37%
63%


ORD-SFO
40%
60%


ORD-SLC
43%
57%

From Table 4 UA has a relatively larger market power share in ORD-SEA,ORD-SFO and ORD-SLC compared with AA, especially in ORD-SEA, while UA's market power is 63%. In city-pair ORD-SAN, AA has a relatively larger market power which is 59%. We know that when there are only a few agents on one side of a market, for these agents will possess market power and the bigger the market power share, the higher profit it will have, holding other factors constant. One would expect, therefore, that AA would be more profitable in the ORD-SAN market while UA would be more profitable in the other three city pairs.

This chapter has developed a dynamic model of collusion in airport-pair routes airlines and compares the market power between the city-pairs Chicago and San Diego, Chicago and Seattle, Chicago and San Francisco and Chicago and Salt Lake City for United Airlines and American Airlines. We have used a state-space representation that is estimated by Kalman-filtering techniques to specify the first order conditions. The data we use are Databank 1A (DB1A) Department of Transportation (DOT) data. In our model, we discuss the economy-wide exogenous variables and city-pair specific variables.

In this chapter, we only look at all the city pairs in which American and United are dominant firms. In future work, we can extend the chapter to examine richer empirical settings in which, among other things, the city-pair routes are not dominated by two firms and in which exit-entry is impacted by firm conduct and market conditions. Our general framework also appears to be an appropriate and feasible vehicle for examining market conduct in other industries where merger and acquisition activities may be subject to FTC or US department of Justice oversight.

CHAPTER 2[3]

Airline Energy Demand

2.1. Introduction

The U.S. commercial airline industry consumes 4% of the fuel used in the U.S. and understanding what influences the demand for fuel and how to best forecast the airline industry's future energy demands has import to the carriers themselves, for planning and operational decision, but also for world energy markets. Before we focus on a particular facet of energy demand, aircraft jet fuel, we provide a bit of perspective on energy demand (and supply) from an economic point of view. The general issues of what factors drive energy demand, the economics of energy commodities, and the need to have better energy forecasting systems are all important factors in a world where the environmental impacts of global warming are beginning to be acknowledged. This last issues is all the more relevant to the airline industry in light of the recent decision by the European Union to include aviation emissions in its CO2 cap and trade program (Wall Street Journal, June 6, 2011) "EU Holds Ground on Airline CO2 Cap; Trade War Coming?"). In this plan not only will European (EU) airlines be given CO2 limits and will pay penalties of EUR100/ton for CO2 emissions above their allotment, but the limits will also be binding

[3] Chapter 2 is partially based on Fang, Y, Sickles, R.C. (2008b)

on US airlines who have European operations. Clearly such a program, and any others that require counterfactual analysis of energy demand, specifically aircraft jet fuel demand, can only be analyzed on the basis of a structural model, such as the one we have developed in the previous chapter.

The study of the economics of energy resources and energy commodities includes the factors and forces motivating firms and consumers to supply, convert, transport, use energy resource; market and regulatory structures; distributional and environmental consequences; economically efficient use. Energy demand is derived from preferences for energy services to both industry and the household and depends on properties of conversion technologies and costs. The fact that energy use is dominantly depletable resources, particularly fossil fuels, makes this chapter unique. The energy industry has moved into the 21st century with promises of both profits and a short-term future. Exploration and production technology is constantly improving, creating the ability to find oil and gas in increasingly remote and inaccessible locations. With added pressure from government, cleaner fuels are being introduced on a continual basis. Additionally, the expanding energy demand from developing countries is changing the energy market.

From December 1 through 11, 1997, more than 160 nations met in Kyoto, Japan, to negotiate binding limitations on greenhouse gases for the developed nations, pursuant to the objectives of the Framework Convention on Climate Change of 1992. The outcome of the meeting was the Kyoto Protocol, in which the developed nations agreed to limit their greenhouse gas emissions, relative to the levels emitted in 1990. The United States agreed to reduce emissions from 1990 levels by 7% during the period 2008 to 2012.

Energy is crucial to the economic progress and social development of nations. Energy can be neither created nor destroyed but can be converted among forms. Energy comes from the physical environment and ultimately returns there. The demand for energy is a derived demand. The value of energy is assessed by its ability to provide a set of desired services in both industry and in the household.

Energy commodities are economic substitutes. Energy resources are depletable or renewable and storable or non-storable. On a global scale the 20th century was dominated by the use of fossil fuels. According to the US department of Energy, in the year 2000 global commercial energy consumption consisted of Petroleum (39%), coal (24%), natural gas (23%), hydro (6%), nuclear (7%) and others (1%). In 1999, the total sources of energy consumed in the United States, 92% was from a depletable resource and only 8% was from a renewable resource. No one doubts that fossil fuels are subject to depletion, and that depletion leads to scarcity, which in turn leads to higher prices. Resources are defined as "nonconventional" when they cannot be produced economically at today's prices and with today's technology. With higher prices, however, the gap between conventional and nonconventional oil resources narrows. Ultimately, a combination of escalating prices and technological enhancements can transform the nonconventional into conventional. Much of the pessimism about oil resources has been focused entirely on conventional resources.

Demand for Energy

Energy security refers to loss of economic welfare that may occur as a result of a change in the price of availability of energy. Bohi and Toman (1996) suggest a link between energy and economy. An abundance of empirical research supports that a strong correlation between increases in oil prices and decreases in macroeconomic performance for oil-importing industrialized countries.

Industrial energy demand increases most rapidly at the initial stages of development, but growth slows steadily throughout the industrialization process (Medlock and Soligo, 2001). Energy demand for transportation rises steadily, and takes the majority share of total energy use at the latter stages of developments.

In fact, almost every recession in the post-World War II era in the United States, as well as many other energy-importing nations, has been preceded by a spike to the price of energy (Hamilton, 1983, Ferderer, 1996 and Mork, Mysen, and Olsen, 1994)

Strong economic growths across the globe and new global demands for more energy have meant the end of sustained surplus capacity in hydrocarbon fuels and the beginning of capacity limitations. In fact, the world is currently precariously close to utilizing all of its available oil-production capacity, raising the chances of an oil-supply crisis with more substantial consequences then seen in three decades. These limits mean that America can no longer assume that oil-producing states will provide more oil. Nor is it strategically and politically desirable to remedy our present tenuous situation by simply increasing our dependence on a few foreign sources. As a result, the expanding demand for energy will change U.S. policy toward the Middle East, Russia and China. A recent example is that the state-owned Chinese company CNOOC eventually abandons Unocal bid due to strong political opposition in the US.

Elasticity of energy demand

Is Energy an essential good? In economics, an essential good is one for which the demand remains positive no matter how high its price becomes. Energy is often described as an essential good because human activity would be impossible absent use of energy. Energy is essential to humans, neither particular energy commodities nor any purchased energy commodities are essential goods because consumers can convert one form of energy into another.

The income elasticity of energy demand is defined as the percentage change in energy demand given a one percent change in income holding all else constant, or

$$\varepsilon_y = \frac{\%\Delta e}{\%\Delta y} = \frac{de}{dy} \cdot \frac{y}{e}$$

where e denotes energy demand and y denotes income. "The household sector's share of aggregate energy consumption tends to fall with income, the share of transportation tends to rise, and the share of industry follows an inverse-U pattern." (Judson, Schmalensee and Stroker,1999)

The price elasticity of energy demand is defined as the percentage change in energy demand given a one percent change in price holding all else constant, or

$$\varepsilon_p = \frac{\%\Delta e}{\%\Delta p} = \frac{de}{dp} \cdot \frac{p}{e}$$

where p denotes the price of energy.

Cooper (2003) uses a multiple regression model derived from an adaptation of Nerlove's partial adjustment model to estimate both the short-run and long-run elasticity of demand for crude oil in 23 countries. The estimates so obtained confirm that the demand for crude oil internationally is highly insensitive to changes in price.

Demand Substitution Between Energy Commodities and others

Denny, Fuss, and Waverman (1981) used time-series data for 18 U.S. manufacturing two digit industries (1948-71) and 18 Canadian manufacturing industry groups (1962-75). Their results were also mixed: for both U.S. and Canada, energy and capital were substitutes in the food industry, but they were complements in the tobacco industry.

Energy consumption can be modeled as either providing utility to households or as an input in the production process for firms. Expressing the former problem mathematically, we have that a representative consumer maximizes utility, $U(z,e)$, which is function of energy consumption, e, and all other consumption, z, subject to the constraint that expenditures cannot exceed income, y. Let the energy variable be a vector of n energy products, $e=(e_1,e_2,...,e_n)$, we could examine the substitution possibilities across energy products. Allowing the price of good j to be represented as p_j, the consumer is assumed to

$$\max_{z,e_1,...e_n} U(z,e_1,...e_n)$$

subject to: $y \geq p_z Z + p_{e_1} e_1 + ... + p_{e_n} e_n$

The first order necessary conditions for a maximum for this problem can be solved to yield demand equations for each of the energy products and for all other consumption. With some adjustments, the above method can be applied to a representative firm.

Recent research focuses mainly on dynamic models. Dynamic models allow for a more complete analysis of the energy demand because they are capable of capturing factors that generate the asymmetries. In addition, dynamic models incorporate the intertemporal choices that a consumer/firm must make when maximizing utilities/profits over some time horizon. Medlock and Soligo (2002) developed a useful framework. Let z_t be multiple types of capital and e_t be multiple types of energy consumption. Denoting time using the subscript t the consumer will maximize the discounted sum of lifetime utility, $\sum_{t=0}^{T} \beta^t U(z_t, e_t)$, subject to the constraint capital goods purchases (i_t), purchases of other goods (z_t), purchases of energy (e_t), and savings (s_t) in each period cannot exceed this period's income (y_t), plus the return of last period's saving ($(1+r)s_{t-1}$). It is assumed that capital goods depreciate at a rate δ, savings earn a rate return r, the discount rate is $0 < \beta < 1$, and all initial conditions are given.

Consumers will

$$\max_{z,e,s} \sum_{t=0}^{T} \beta^t U(z_t, e_e)$$

subject to $p_{zt} z_t + p_{et} e_t + p_{kt} i_t + s_t \le y_t + (1+r)s_{t-1}$

$$i_t = k_t - (1-\delta)k_{t-1}$$

$z_t, u_t, k_t \ge 0$ for $t = 1, \ldots, T$

World Energy Demand Outlook

According to EIA, world energy consumption is projected to increase by 57% from 2002 to 2025. World oil use is expected to grow from 78 million barrels per day in 2002 to 103 million barrels per day in 2015 and 119 million barrels per day in 2025. The projected increment in worldwide oil use would require an increment in world oil production capacity of 42 million barrels per day over 2002 levels. Members of the OPEC are expected to be the major suppliers of the increased production that will be required to meet demand, and they account for 60% of the projected increase in world capacity. In addition, non-OPEC suppliers are expected to add nearly 17 million barrels per day of oil production capacity between 2002 and 2025. Substantial increments in new non-OPEC supply are expected to come from the Caspian Basin, Western Africa, and Central and South America.

Natural gas is projected to be the fastest growing component of world primary energy consumption. Consumption of natural gas worldwide increases in the forecast by an average of 2.3% annually from 2002 to 2025, compared with projected annAAl growth rate of 1.9% for oil consumption and 2.0% for coal consumption. From 2002 to 2025, consumption of natural gas is projected to increase by 69%, and its share of total energy consumption is projected to grow from 23% to 25%. Natural gas is seen as a desirable alternative for electricity generation in many parts of the world, given its relatively efficiency in comparison with other energy sources, as well as the fact that it burns more cleanly than either coal or oil and thus is an attractive alternative for countries pursuing reductions in greenhouse gas emission.

World coal consumption is projected to increase at an average rate of 2.5% per year. From 2015 to 2025, the projected rate of increase in world coal consumption slows to 1.3% annually. Coal is expected to maintain its importance as an energy source in both the electric power and industrial sectors.

Hydroelectricity and other renewable energy sources are expected to maintain 8% share of total energy use worldwide throughout the projection period. Much of the projected growth in renewable electricity generation is expected to result from the completion of large hydroelectric facilities in emerging economies, particularly in Asia.

Energy Supply

The study of depletable resource economics began with articles by L. Grey (1914) and H. Hotelling (1931), which examined economically inter-temporal optimal extraction from a perfectly known stock of the resource, with perfectly predictable future prices of the extracted commodity. Sweeney (1977) and Stiglitz (1976) both clarified the Hotelling rule in the presence of monopoly, and Gilbert and Richard (1978) and Salant (1976) extended this to the case of a dominant producer with a competitive fringe and several dominant producers, analogous to the case of OPEC. Pindyck (1982) and Kolstad (1994) extended the model to several imperfectly substitutable exhaustible resources.

In the years following the 1973 oil price rise, U.S. energy policy could be characterized as generally suspicious of the market. Supply augmentation was a major strategy pursued by the U.S. government in addressing the "energy crisis." The security dimensions of energy supply have always been viewed as appropriate concerns of the government. One could argue that the Gulf War in the early 1990s was simply a form of energy policy, protecting western oil supplies originating in the Middle East. Countries other than the United States (such as Japan, China) have tried to diversify their sources of energy to reduce the risk of disruption.

Security was also viewed as threatened by sudden fluctuations in the price of oil: thus the establishment of the Strategic Petroleum Reserve (SPR). The idea is that if the price of oil were to rise rapidly due to disruption in supply, then the SPR could be called upon to provide supplies, thus reducing the price shock.

But depletable resource use cannot dominate forever. Therefore, a future transition from depletable resources, particularly from fossil fuels, is inevitable. However, which renewable energy sources will dominate future consumption is unclear. And there is great uncertainty about the timing of a shift to renewable energy resources. Although this is a formidable question, Wiser, R., Olson, S., Bird, L., and Swezey, B. (2004) introduce green pricing programs, which represent one way that consumers can voluntarily support renewable energy. Their analysis yields several interesting results: Program duration impacts customer response. The longer a program has been operating, the more likely its message has spread and the higher the probability of strong program success. Higher purchase thresholds for residential customers should be considered. Initial customer participants in green pricing programs may not be highly sensitive to cost, and may be willing to purchase higher quantities of renewable energy. Therefore, this is the case for those utilities focused on maximizing renewable energy sales, not customer participation rates. Price premiums and minimum monthly costs are not the primary determinants of program success. Price may become a more important determinant as green pricing programs expand to target more than the early innovator customers. And smaller utilities appear to have a greater likelihood of achieving success.

The prospect of producing clean, sustainable power in substantial quantities from renewable energy sources is arousing renewed interest worldwide. Hydroelectricity is the only renewable energy source today that makes a large contribution to world energy production. The long-term technical potential is believed to be 9 to 12 times current production, but increasingly, environmental concerns block new dams. The large areas affected may have a negative environment impact. Hydroelectricity dams, like the Aswan Dam, have adverse consequences both upstream and downstream. Wind power is one of the most cost competitive renewable sources today. Its long-term technical potential is believed 5 times current global energy consumption. But this requires 12.7% of all land area with certain height. Geothermal power and tidal power are the only renewable sources not dependent on the sun but are today limited to special locations. Most renewable sources are diffuse and require large land areas and great quantities of construction material for significant energy production. There is some doubt that they can be built out rapidly enough to replace fossil fuels. The large and sometimes remote areas may also increase energy loss and cost from distribution. On the other hand, some forms allow small-scale production and may be placed very close to or directly at consumer households, businesses, and industries. We may forecast the coexistence of multi-renewable energy sources in the future. Boyle (1996) provides a comprehensive overview of the principal renewable energy sources: solar thermal, biomass, tidal, wave, photovoltaic, hydro, wind, and geothermal.

World Oil Market

The Organization of the Petroleum Exporting Countries (OPEC) comprises countries that have organized for the purpose of negotiating with oil companies on matters of Petroleum production, prices, and future concession rights. Founded September 14, 1960 at a Baghdad conference, OPEC originally consisted of only five countries: Iran, Iraq, Kuwait, Saudi Arabia and Venezuela, but has since expanded to include several others: Algeria, Indonesia, Libya, Nigeria, Qatar, and United Arab Emirates. The members of OPEC, which constitute a cartel, agree on the quantity and the prices of the oil exported. OPEC seeks to regulate oil production, and thereby manage oil prices, primarily by setting quotas for its members. Member countries hold about 75% of the world's oil reserves, and supply 40% of the world's oil. Since worldwide oil sales are dominated in U.S. dollars, changes in the value of the dollar against other world currencies affect OPEC's decisions on how much oil to produce. After the introduction of the eruo, Iraq unilaterally decided it wanted to be paid for its oil in euros instead of U.S. dollars. OPEC decisions have a heavy influence on international oil prices. A good example is 1973 energy crisis, in which OPEC refused to ship oil to western countries that had supported Israel its conflict with Egypt, the Yom Kippur War. This refusal caused a fourfold increase in oil price, which lasted five months, starting on October 17, 1973, and ending on March 18, 1974. OPEC nations then agreed on January 7, 1975, to raise crude oil prices by 10%. Unlike many other cartels, OPEC has been successful at increasing the price of oil for extended periods. Much of OPEC's success can be attributed to Saudi Arabia's flexibility. It has tolerated cheating on the part of other cartel members, and cut its own production to compensate for other members have exceeded their production quotas. This actually gives them good leverage, because with most members at full production, Saudi Arabia is the only member with spare capacity, and the ability to increase supply, if needed. The policy has been successful. However, OPEC's ability to raise prices does have some limits. An increase in oil price decreases consumption, and could cause a net decrease in revenue. Furthermore, an extended rise in price could encourage systematic behavior change, such as alternative energy utilization, or increased conservation. As of August 2004, OPEC has been communicating that its members have little excess pumping capacity, indicating that the cartel is losing influence over crude oil prices.

The six major non-OPEC oil-producing nations are: Norway, Russia, Canada, Mexico, the United States and Oman. Russian production increases dominated no-OPEC production growth from 2000 forward and was responsible for most of the non-OPEC increases since the turn of the century. In 2001, a weakening U.S. economy and increases in non-OPEC production put downward pressure on prices. In response OPEC once again entered into a series of reductions in member quotas cutting 3.5 million barrels by September 1, 2001. In the absence of the September 11, 2001 terrorist attack this would have been sufficient to moderate or even reverse the trend. In the wake of the attack the crude oil price plummeted. Under normal circumstances a drop in price of this magnitude would have resulted in another round of quota reductions but given the political climate OPEC delayed additional cuts until January 2002 when it reduced its quota by 1.5 million barrels per day and was joined by several non-OPEC producers including Russia who promised combined production cuts of an additional 462,500 barrels. This had the desired effect with oil prices moving into the $25 range by March 2002. By mid-year the non-OPEC members were restoring their production cuts but prices continue to rise and U.S. inventories reached a 20-year low later in the year. By yearend oversupply was not a problem. Problems in Venezuela lead to a strike at PDVSA causing Venezuelan production to plummet. In the wake of the strike Venezuela was never able to restore capacity to its previous level and is still about 900,000 barrels per day below its peak capacity of 3.5 million barrels per day. On March 19, 2003, just as some Venezuelan production was beginning to return, military action commenced in Iraq. Meanwhile, inventories remained low in the U.S. and other OECD countries. With an improving economy U.S. demand was increasing and Asian demand for crude oil was growing at a rapid pace. The loss of production capacity in Iraq and Venezuela combined with increased production to meet growing international demand led to the erosion of excess oil production capacity, but by mid 2003 the excess was below 2 million. During much of 2004 and 2005 the spare capacity to produce oil has been less than one million barrels per day. A million barrel per day is not enough spare capacity to cover an interruption of supply from almost any OPEC producer. In a world that consumes over 80 million barrels per day of petroleum products that add a significant risk premium to crude oil price and is largely responsible for prices in excess of $40 per barrel. Readers who are interested in The History of World Oil Market and Prices: 1970-2004 could find more material from (EIA).

Energy, Economy and Environment

Many important environment damages stem from the production, conversion, and consumption of energy. Costs of these environmental damages generally are not incorporated into prices for energy commodities and resources; this omission leads to overuse of energy. It has been shown that estimates of damage costs resulting from combustion of fossil fuels, if internalized into the price of the resulting output of electricity, could clearly lead to a number of renewable technologies being financially competitive with generation from coal plants. Environmental impacts currently receiving most attention are associated with the release of greenhouse gases in the atmosphere, primarily carbon dioxide, from combustion of fossil fuels. During combustion, carbon combines with oxygen to produce carbon dioxide, the primary greenhouse gas. Carbon dioxide accumulates in the atmosphere and is expected to result in significant detrimental impacts on the world's climate, including global warming, rises in the ocean levels, increased intensity of tropical storms, and losses in biodiversity. Concern about this issue is common to energy economics, environmental economics, and ecological economics. Cropper and Oates (1992) suggest a treatment of measuring benefits and costs with a review of cases where benefit-cost analyses have actually been used in the setting of environmental standards. Owen (2004) suggests penalizing high pollutant emitting technologies not only creates incentives for "new" technologies, but it also encourages the adoption of energy efficiency measures with existing technologies and consequently lowers pollutants per unit of output.

Over the past several decades, rising concentrations of greenhouse gases have been detected in the Earth's atmosphere. It has been hypothesized that the continued accumulation of greenhouse gases could lead to an increase in the average temperature of the Earth's surface and cause a variety of changes in the global climates, see level, agricultural patterns, and ecosystems that could be, on net, detrimental.

World carbon dioxide emissions are expected to increase by 1.9% annually between 2001 and 2025. Much of the increase in these emissions is expected to occur in the developing countries. The U.S. produces about 25% of global carbon dioxide emissions from burning fossil fuels, primarily because of its largest economy in the world and 85% of its energy needs through burning fossil fuels. The U.S. is projected to lower its carbon intensity by 25% from 2001 to 2025. There are numerous proposals aiming at reducing the carbon dioxide emissions. Kyoto Protocol is a famous and influential one. Some current estimates indicate that if successfully and completely implemented, the Kyoto Protocol is predicted to reduce the average global rise in temperature by somewhere between 0.02 centigrade and 0.28 centigrade by the year 2050. (Source: Nature, October 2003), compared to the increase of 1.4 centigrade to 5.8 centigrade between 1990 and 2100 predicted by the Intergovernmental Panel on Climate Change (IPCC).

Sickles and Jeon (2004) evaluate the role that undesirable outputs of the economy, such as carbon dioxide and other greenhouse gases, have on the frontier production process. This chapter also explores implications for growth of total factor productivity in the OECD and Asian economies.

Natural disasters shock the energy market, too. According to the Minerals Management Service (MMS), Gulf of Mexico daily oil production was reduced by 89% as a result of Hurricane Katrina. The MMS also report 72% of daily Gulf of Mexico natural gas production was shut in. In 2004, hurricane Ivan causes lasting damage to the energy infrastructure in the Gulf of Mexico and interrupts oil and supplies to the United States.

U.S. Secretary of Energy Spencer Abraham agrees to release 1.7 million barrels of oil in the form of a loan from the Strategic Petroleum Reserve.

2010 BP Deepwater Horizon disaster happened, which eventually dumped five million barrels of oil into the Gulf of Mexico. This had a huge affect on the environment and the damage is still being assessed. This largest accidental marine oil spill in the history of the oil industry results in a speed up demand on clean oil, which might reshape the energy demand scope in the following decades.

The world runs on energy, primarily energy generated from coal and petroleum. The war against terrorism and the tensions in the Middle East have raised new questions about the reliability of America's oil supply from that region. Also concerns about global climate change have focused increased attention on the search for cleaner fuels and energy-generating methods. Russia's determination to become a major petroleum supplier, OPEC's periodic moves to restrict oil production and the rising energy needs in China and other developing countries. These are all important issues forming the future World Energy Market.

2.2. Airline Energy Demand Forecasts

Most aviation fuels are jet fuels originating from crude oil. Crude oil must be refined to be useful and jet fuel is only one of many products that can be derived from crude oil. Jet fuel is extracted from the middle distillates fraction and competes, for example, with the production of diesel.

Crude oil is a limited natural resource subject to depletion and several reports indicate that the world's crude oil production is close to the maximum level and that it will start to decrease after reaching this maximum. A post Kyoto political agenda to reduce oil consumption will have the same effect on aviation fuel production as a natural decline in the crude oil production. On the other hand, it is predicted by the aviation industry that aviation traffic will keep on increasing.

Air traffic has been increasing by mean annual growth rates comprised between 5% and 6% since the middle of the 1980s. This growth is supposed to continue in the coming decade. In a scare energy resources environment, this strong and rapid growth of air transport may be problematic (IPCC, 1999, 2007a, 2007b), which leads to an increased interest for policy makers. Cheze, B. et al. (2011) shows that energy efficiency improvements allow reducing the effect of air traffic rise on the increase in jet fuel demand, but do not annihilate it. Jet fuel demand is thus unlikely to diminish unless there is a radical technological shift, or air travel demand is restricted.

Today global oil production is roughly 81.5 million barrels per day. There are many different methodologies for predicting future crude oil production, all relying on different assumptions and ideas (Bentley and Boyle, 2007). Some are more optimistic when it comes to the amount that can be produced than others. Oil production forecasts from IEA(2008a), Aleklett and Campbell (2003) and Robelius (2007) are taken as representative scenarios for future oil production. The aviation fuel part of crude oil production is assumed to be a fixed percentage in each scenario.

Jet fuel demand and aviation traffic growth are not strictly correlated, since the efficiency of aircraft and air traffic management are improving. The aviation industry actually has experience a huge development since the first commercial aircraft in service. Sicne the 1960s aircraft are 75% quieter and have reduced fuel consumption by 70%.

Overviews of different forecasting methods have been done previously (Bentley and Boyle, 2007; Brandt, 2007; Carlson, 2007), and all of the models have their strengths and weaknesses. Bentley and Boyle concluded that the group of models that predict the peak in crude oil production before 2020 are the most realistic.

The most well known scenario for future oil production is delivered by International Energy Agency (IEA) in its yearly publication World Energy Outlook (WEO). This scenario is based on a growing global economy and that growth needs more oil. In WEO 2008 (IEA 2008a) the increase in oil use till 2030 is divided between 1.3 percent for 2009 to 2020 and then 1.0 percent to the end of the period. The next step is to find production to fulfill demand. This "Business as Usual" (BAU) is called Alternative 1. Alternative 2 is a depletion model, called the "Campbell depletion model". The model and the results can be found in Campbell (2008). Alternative 3, crude oil production forecast from the "Uppsala giant field model" (Robelius, 2007)

In the second chapter of the dissertation, we focus on the use of our structural model for purposes of forecasting energy demands. Energy demands for commercial airlines have been addressed by Greene (1992), Faquih (2008) and etc. but none have used a structural model as ours.

2.3. Data

We use Databank 1A (DB1A) Department of Transportation (DOT) quarterly data during the period 1979I -1988IV (40 quarters) with a set consisting of 2 airlines with subscripts described by their tow letter ticket codes: American (AA) and United (UA). We select four city-pairs that American (AA) and United (UA) are dominant players. The four city pairs are described by their three letter Airport Codes: Chicago O'hare International (ORD)-San Diego International Airport (SAN), Chicago O'hare International (ORD)-Seattle-Tacoma International (SEA), San Francisco International (SFO) and Chicago O'hare International (ORD)-Salt Lake City International (SLC). The variables we used to estimate the structural model are average cost when the route is defined by the city pair (avcstcty), average price when the route is a city pair (avgprcty), and the number of passengers on a route (rtpass). We use national per capita income (pcinc) as an economy-wide exogenous variable and Herfindahl index for city pair (herfcty) as a city-pair specific exogenous variable. We use Gauss as our statistical tool to estimate the structural market power model. For Airline Energy Demand, we tried three approaches. First, Trendline: we simply use time (t) as a variable. Second, Structural model: we use GDP and Oil Price data from Bureau of Economic Analysis and U.S. Energy Information respectively. We also control for seasonal factors by including dummy variables for the first, second and third quarters of each year. The inputs are the number of passengers on a route (rtpass) and Energy Price. Third, ARIMA: we used lags of energy demand and lags of the errors as independent variables.

We use data from 1980-I to 1988-IV as baseline to predict the energy forecast from 1989-I to 1994-III. Three types of energy forecasts: Trend line, Structural model and ARIMA are compared to actual.

First, let's look at trend lines. Trend lines are graphical representations of trends in data that you can use to analyze problems of predictions. Such analysis is also called regression analysis. By using regression analysis, we can extend a trend line in a chart beyond the actual data to predict future values. A linear trend line is a best-fit straight line that is used with simple linear data sets. Your data is linear if the pattern in its data points resembles a line. A linear trend line usually shows that something is increasing or decreasing at a steady rate.

$$f_t = a + bt$$

f_t= forecast for time t

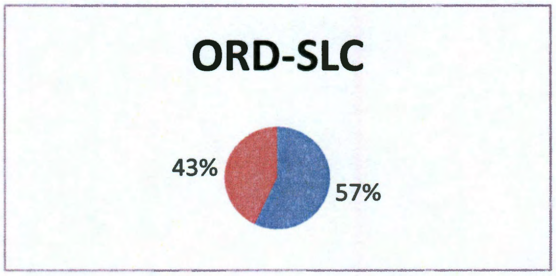
a = intercept of the line

b = the slope of the line

n = # of observations

$$a = \frac{\sum X_t - b\sum t}{n}$$
$$b = \frac{n\sum(tX_t) - \sum t \sum X_t}{n\sum t^2 - (\sum t)^2}$$

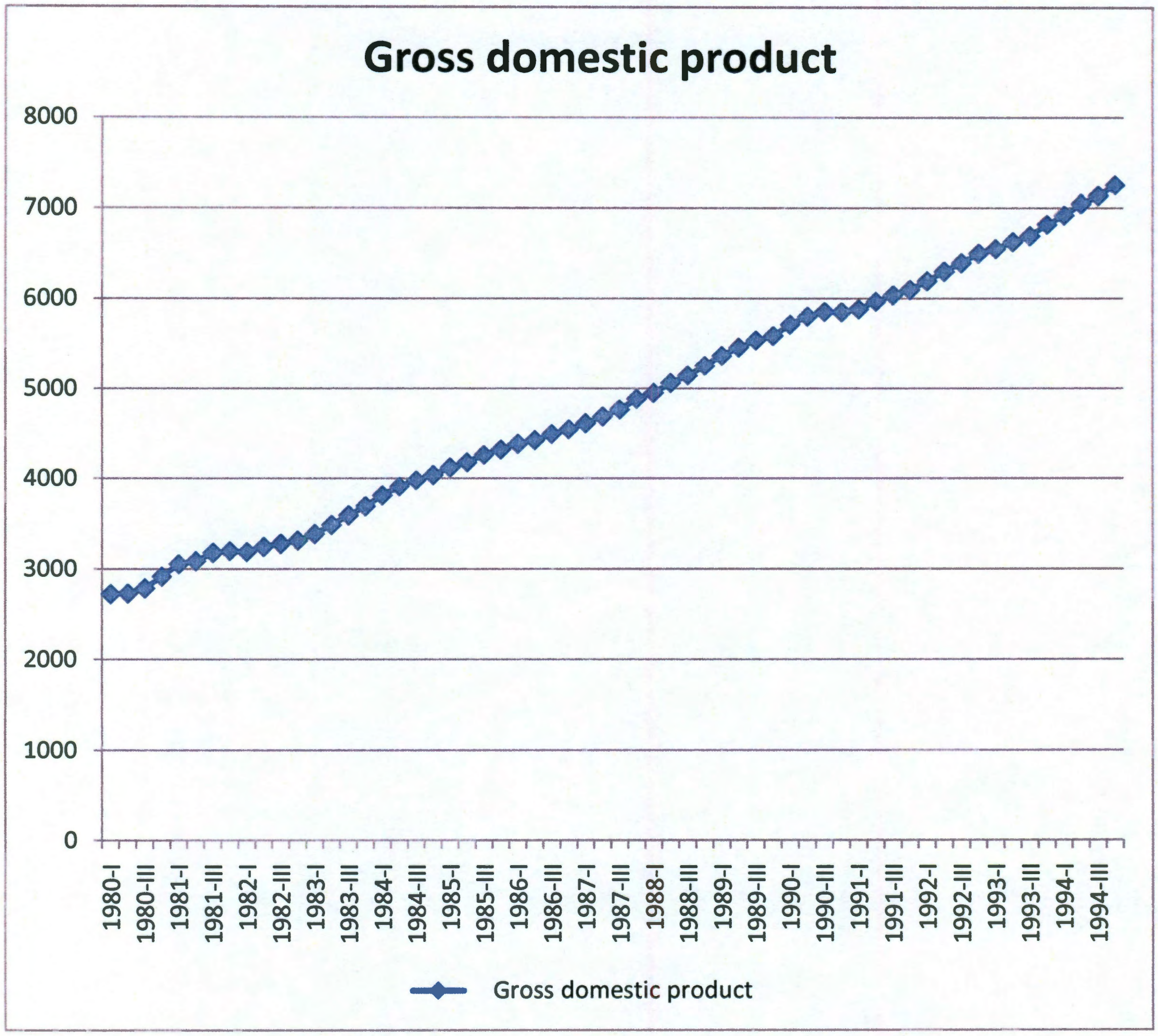
Although trend line projects energy demand in a trend manner, most of time we would like the forecast reflects seasonal impact, as well as GDP and Oil Price. Here introduces a method of structural forecast model that not only will take all into consideration but also apply our market power chapter's findings from the first chapter.



From chapter 1, we know that UA has 57% market power in ORD-SLC market while AA has 43% market power, which is applied to the number of passengers on the route (**rtpass**) forecast. We first use Linear Regression to estimate the coefficients, and then use the market power share chapter's research findings to predict the number of passengers on the route from 1989-I to 1994-III. GDP, Oil Price and quarterly dummies are also included in Structural Model to better track the energy demand pattern. The structural energy forecast model is as below.

$$f_t = \alpha + \beta_1 * rtpass + \beta_2 * Energy\ Price + \beta_3 * GDP + \beta_4 * Oil\ Price + \beta_5 * Q2\ Dummy + \beta_6 * Q3\ Dummy + \beta_7 * Q4\ Dummy$$

Chart 2.3.1 GDP [Billions of dollars] Bureau of Economic Analysis



Oil price data is from U.S Energy Information

Table 2.3.2 AA_ORD_SLC

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.922402952
R Square	0.850827207
Adjusted R Square	0.813534008
Standard Error	3712870.18
Observations	36

ANOVA

	df	SS	MS	F	Significance F
Regression	7	2.20155E+15	3.14508E+14	22.81454109	5.49082E-10
Residual	28	3.85991E+14	1.37854E+13		
Total	35	2.58755E+15			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	24088207.85	13356735.24	1.803450276	0.082088862	-3271823.644	51448239.35	-3271823.644	51448239.35
X Variable 1	-46.06508692	42.89470491	-1.073910801	0.292030748	-133.9309056	41.80073179	-133.9309056	41.80073179
X Variable 2	-2949108.33	2066354.127	-1.427203736	0.164578907	-7181842.826	1283626.166	-7181842.826	1283626.166
X Variable 3	6413.364012	1767.599911	3.628289396	0.001127436	2792.599779	10034.12824	2792.599779	10034.12824
X Variable 4	105620.5997	188746.2963	0.559590317	0.580208229	-281008.6564	492249.8558	-281008.6564	492249.8558
X Variable 5	1164252.001	1938580.201	0.600569427	0.552957432	-2806749.476	5135253.477	-2806749.476	5135253.477
X Variable 6	2256634.198	2094712.456	1.077300224	0.290540615	-2034189.701	6547458.096	-2034189.701	6547458.096
X Variable 7	590988.5944	1809849.234	0.326540235	0.746444022	-3116319.453	4298296.642	-3116319.453	4298296.642

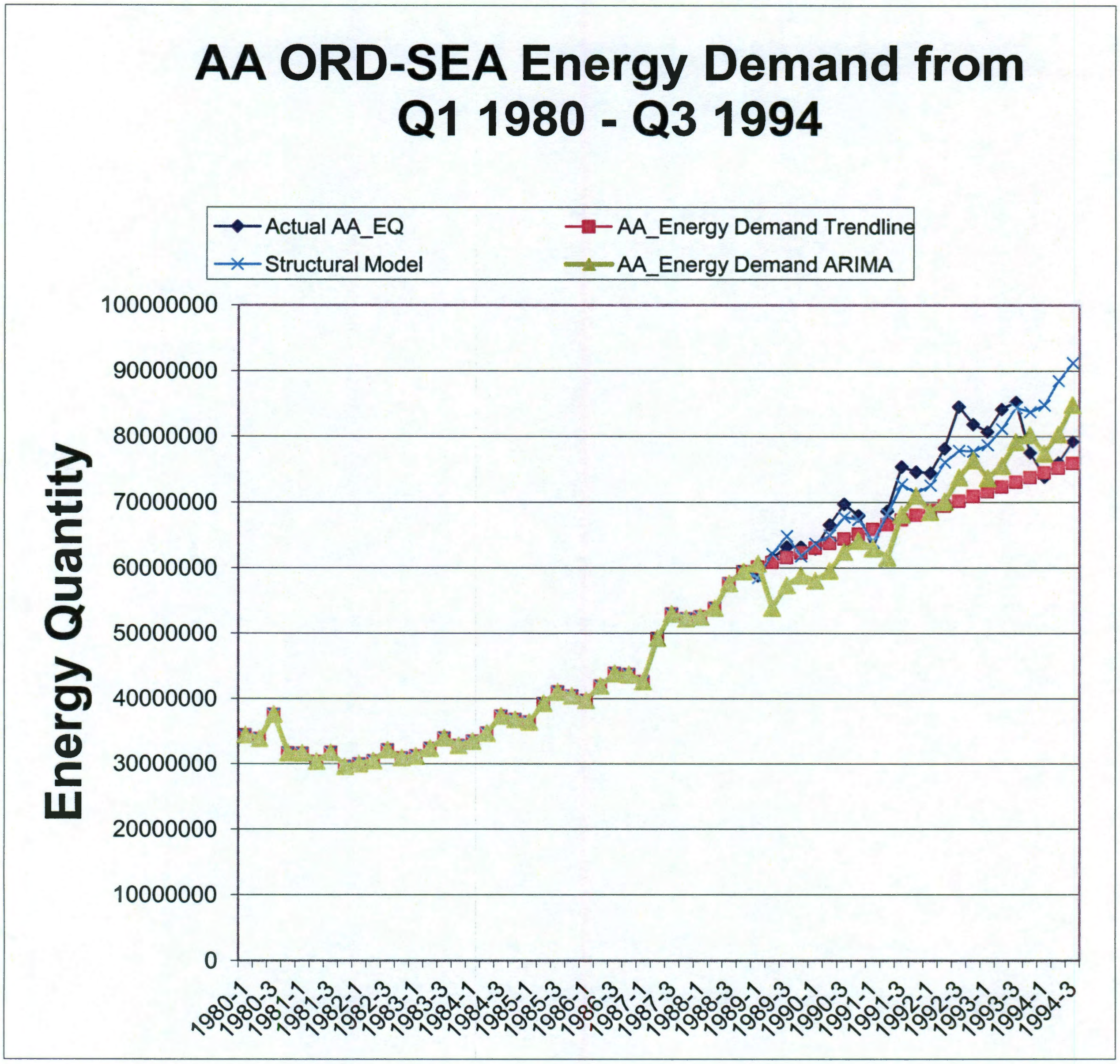
We use data of 1980-I to 1988-IV and ARIMA (1,0,1) to estimate μ, φ and θ.

$$f_t = \mu + f_{t-1} - \theta e_{t-1}$$

And then use average of forecasts from Trend line and structural model to get f_{t-1} and to do energy predication from 1989-I to 1994-III.

Chart 2.3.3 and Chart 2.3.4 display AA and UA ORD-SEA Energy Demand Forecasts using Trend line, ARIMA and Structural model.

Chart 2.3.3


AA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
AA_Energy Demand Trendline
Structural Model
AA_Energy Demand ARIMA
Energy Quantity
100000000
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
1987-1
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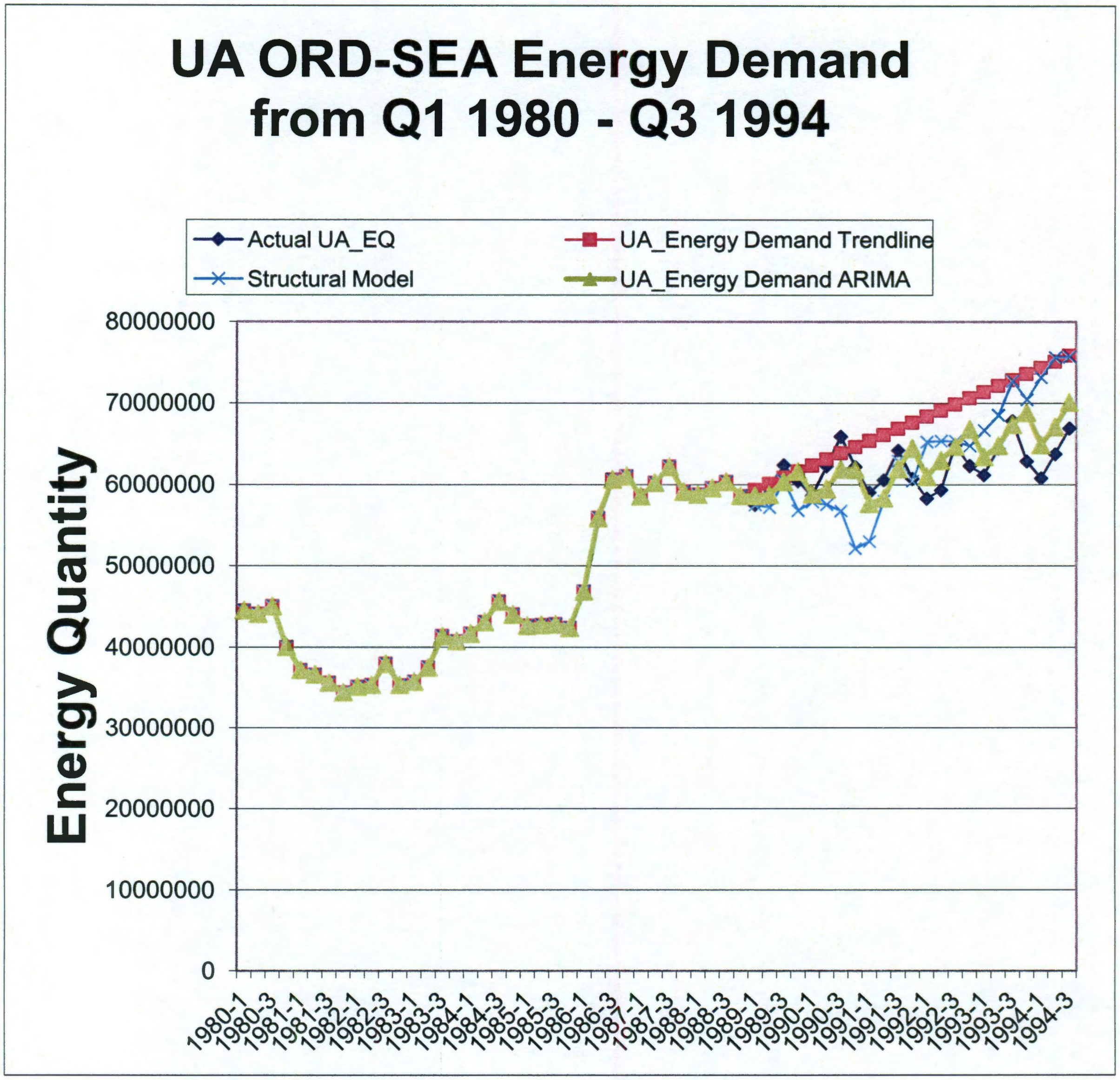
1988-3
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.4


UA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual UA_EQ
UA_Energy Demand Trendline
Structural Model
UA_Energy Demand ARIMA
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
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1988-1
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1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

For AA ORD-SEA, Structural Model shows significant advantage in prediction of turning points and seasonality in these three exercises of forecasts. Trend Line does a good job in predicting the trend. ARIMA underestimate the demand. Therefore, in AA-SEA, our Structural Model forecast beats the other two approaches.

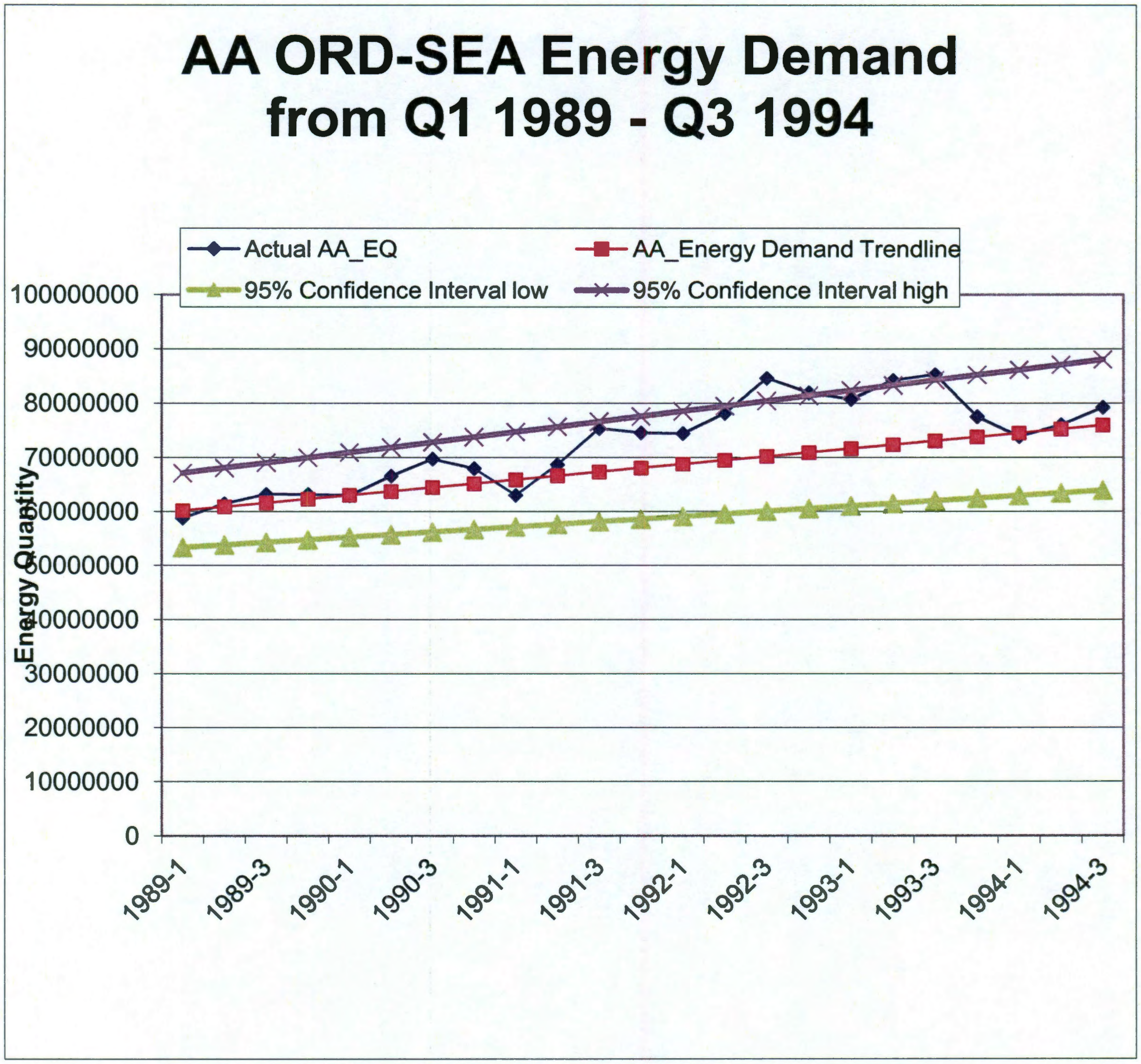
But when we look at the other carrier, UA same market ORD-SEA, ARIMA performs the best among the three exercises.

Chart 2.3.5 to Chart 2.3.10 display 95% confidence intervals of AA and UA ORD-SEA Energy Demand Forecast using Trend line, ARIMA and Structural model.

For AA, the majority actual energy demand falls in 95% confidence interval of Structural Model. For UA, the majority actual energy demand falls in 95% confidence interval of ARIMA.

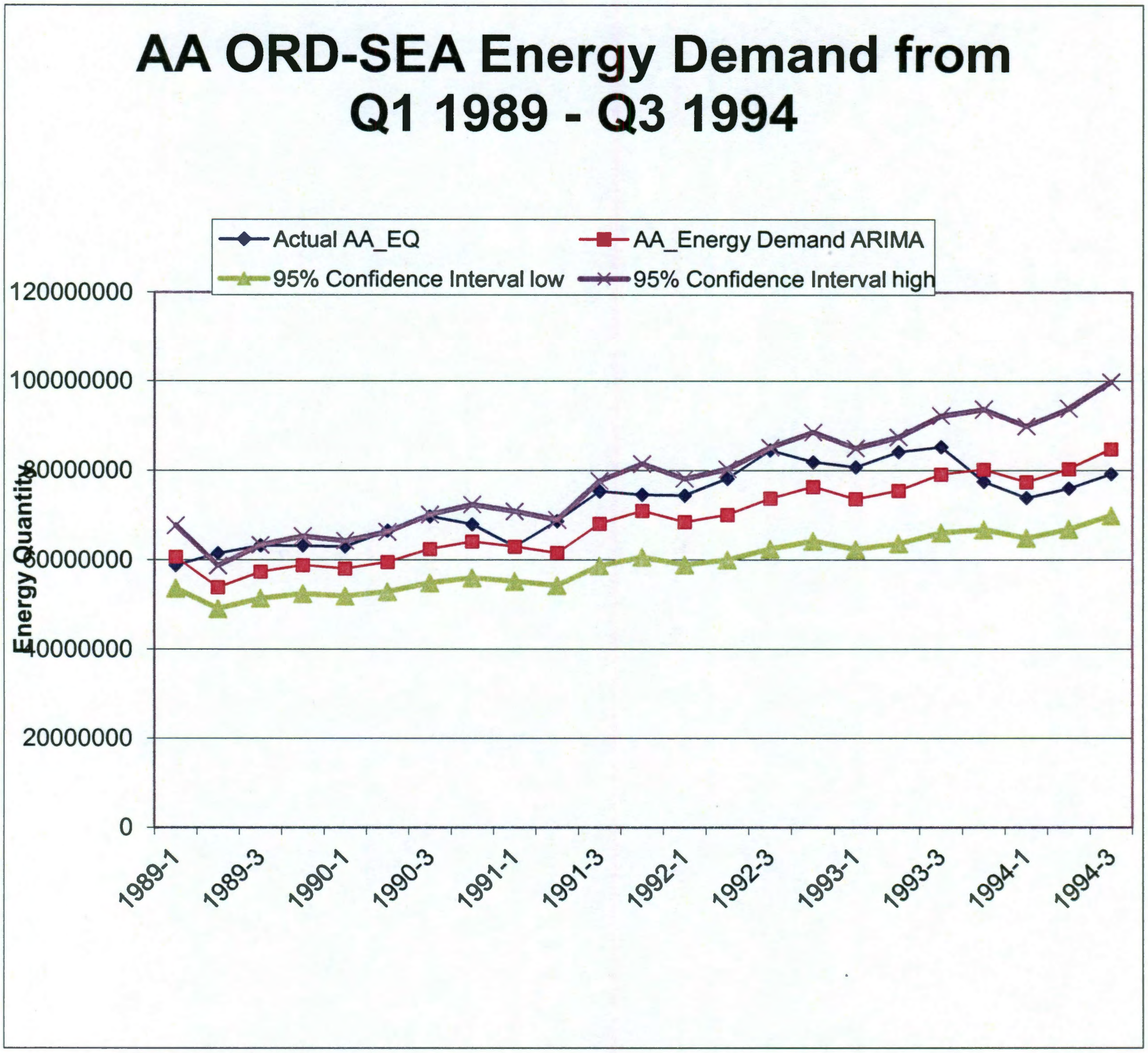
None of these three exercises is a dominant winner. Given this circumstance, the use of model averaging and forecast combination is a better alternative. We will discuss more in chapter 3.

Chart 2.3.5



AA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual AA_EQ
AA_Energy Demand Trendline
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
100000000
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.6



AA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual AA_EQ
AA_Energy Demand ARIMA
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
120000000
100000000
80000000
60000000
40000000
20000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.7

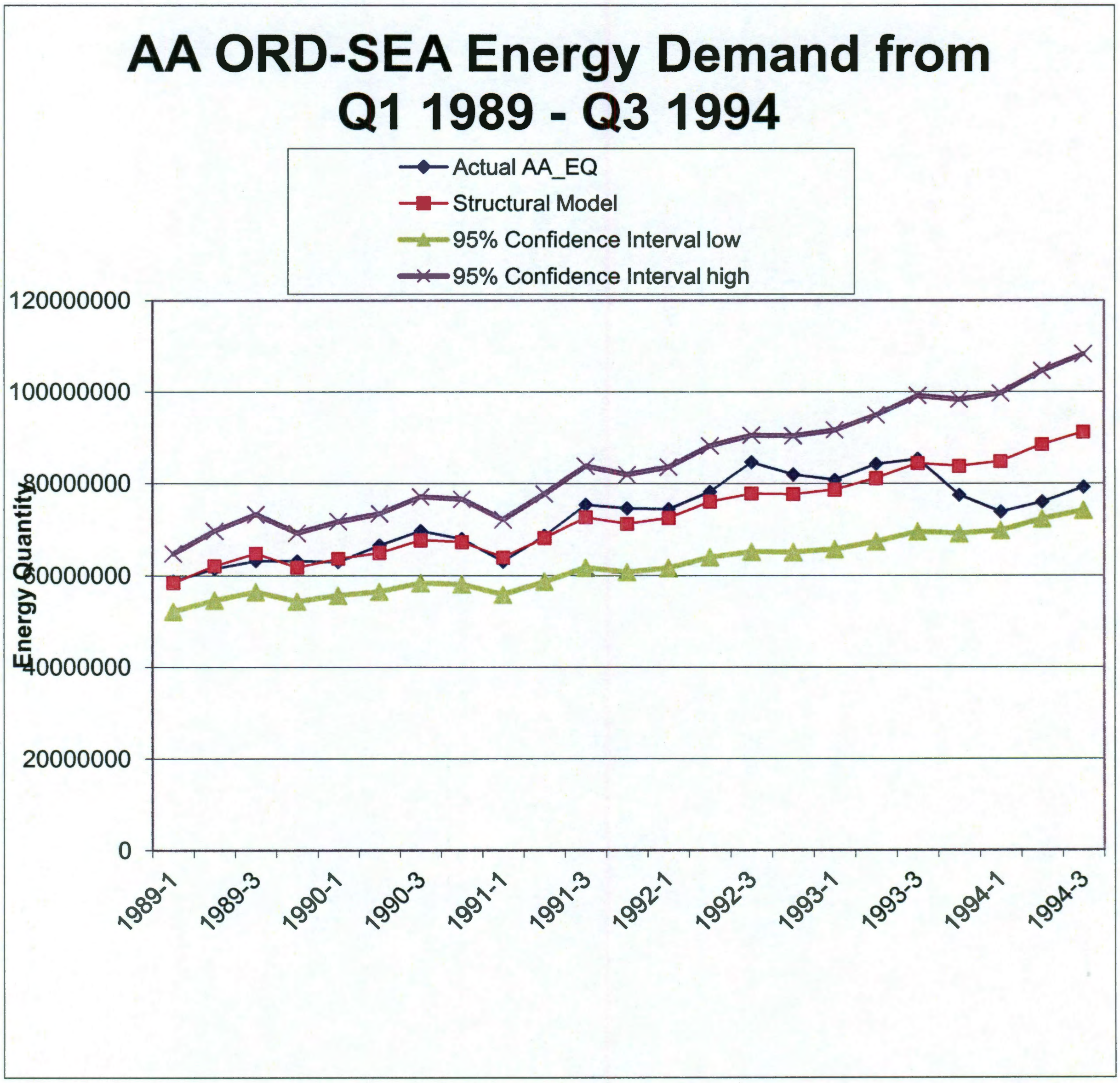

AA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual AA_EQ
Structural Model
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
120000000
100000000
80000000
60000000
40000000
20000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.8

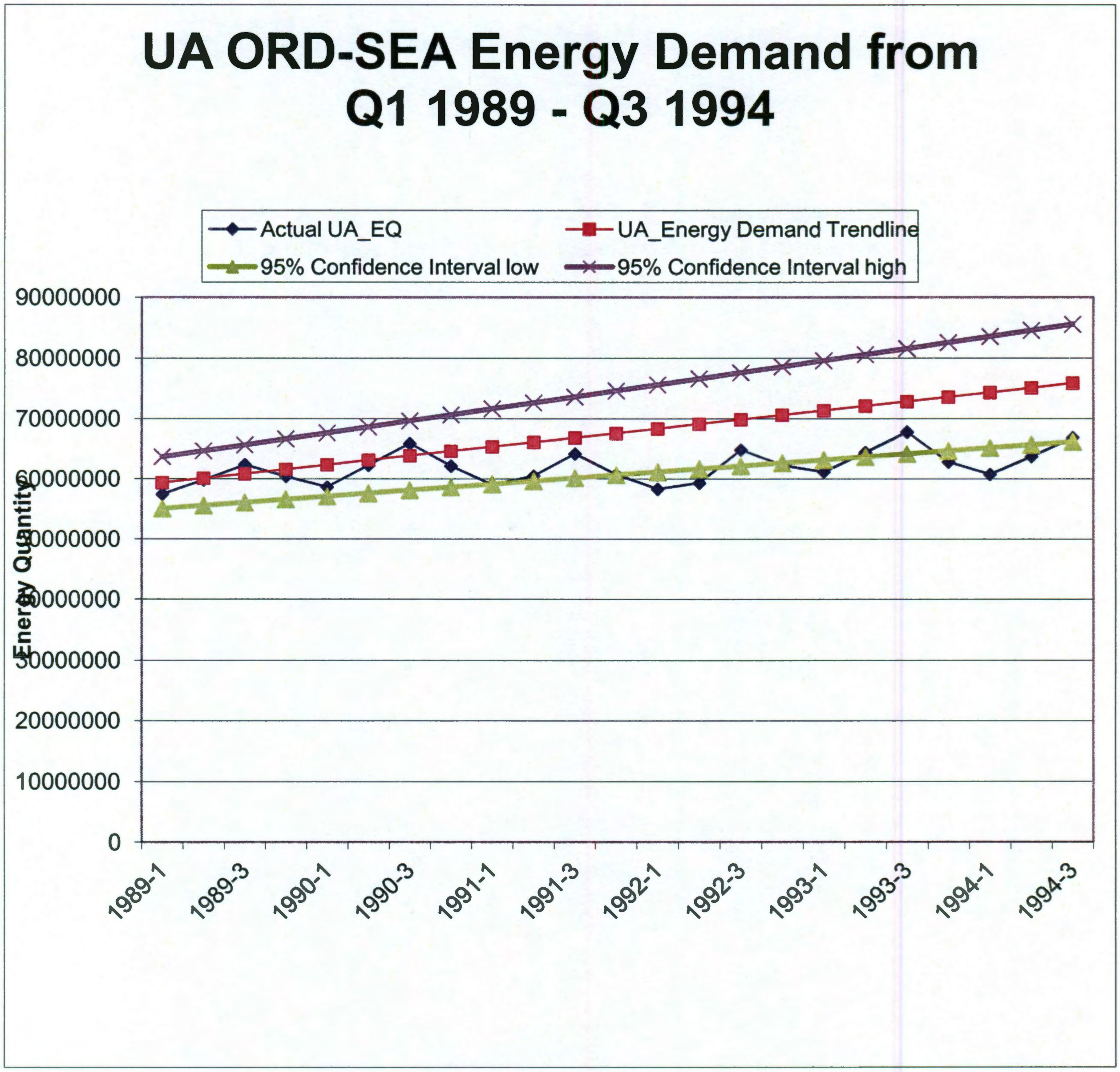

UA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual UA_EQ
UA_Energy Demand Trendline
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.9

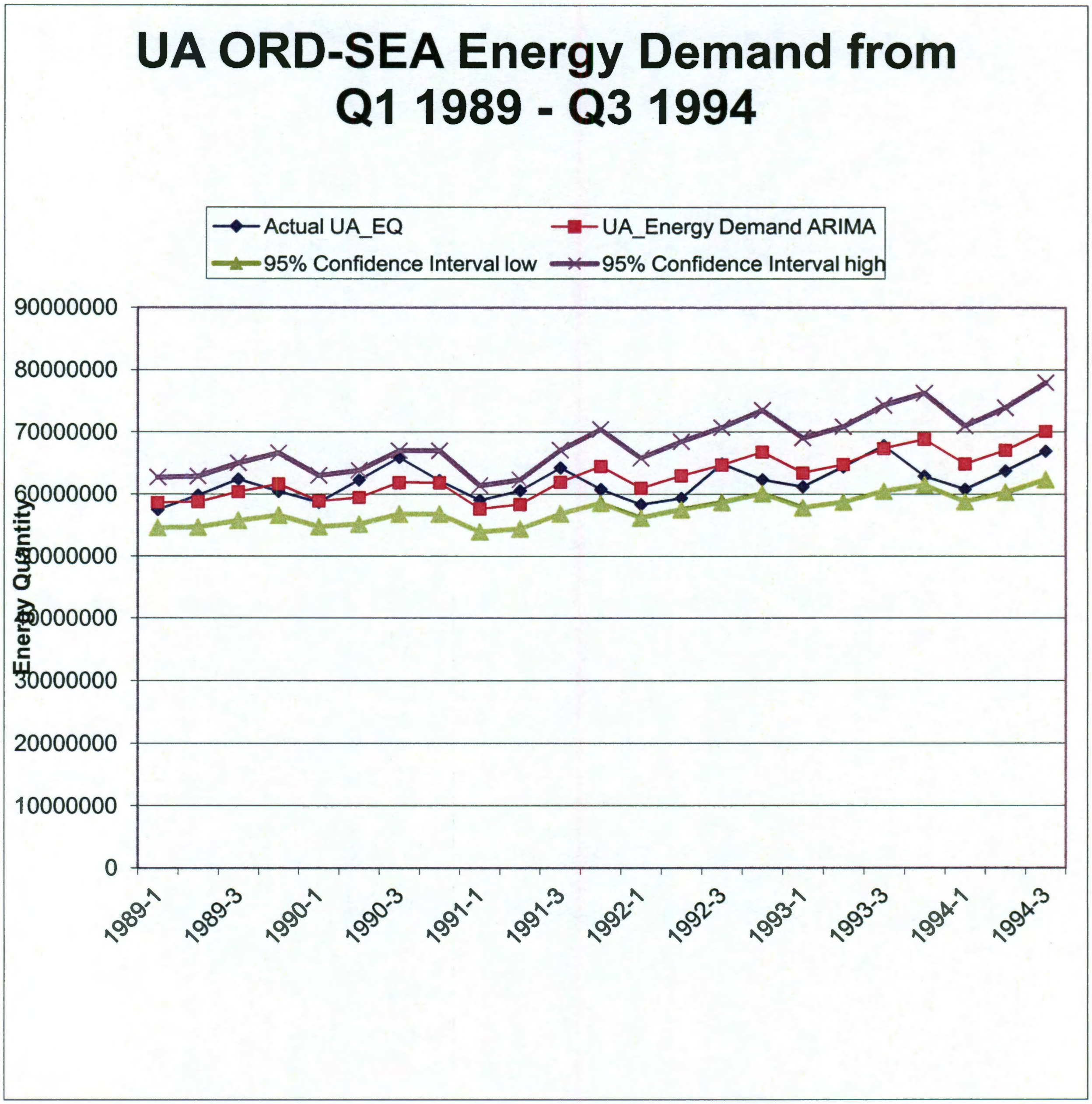
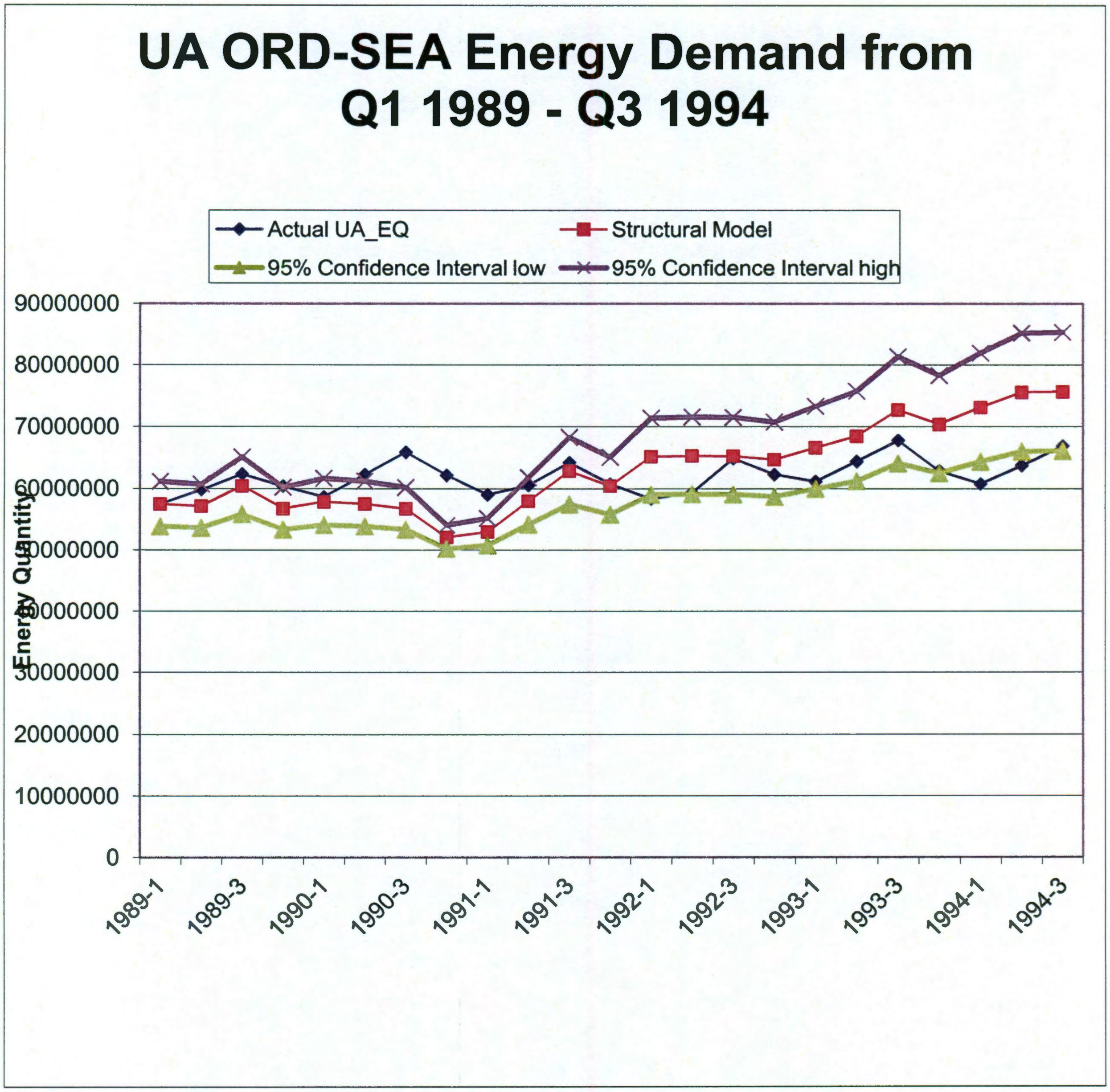

UA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual UA_EQ
UA_Energy Demand ARIMA
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 2.3.10



UA ORD-SEA Energy Demand from
Q1 1989 - Q3 1994
Actual UA_EQ
Structural Model
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
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1993-3
1994-1
1994-3

CHAPTER 3

The Use of Model Averaging and Forecast Combination Techniques in Estimating Jet and Fuel Demand

3.1. Introduction

In Chapter 3, we discuss and utilize various forecasting approaches that combined forecasts using various weighting schemes and we utilize these as well as specific forecast from our structure model, ARIMA time series and simple time trends. A combined estimations or forecasts provide a decisive conclusion instead of a confusion of diversified results. From an academic view, combining estimates, or averaging estimates is certainly a way of providing a solution to modeling uncertainty.

In model selection the data are used to select one of the models under consideration. An alternative to selecting one model and basing all future work on this one model is model averaging. This means estimating the quantity in question via a number of possible models, and forming a weighted average of the resulting estimators.

Bayesian model averaging computes posterior probabilities for each of the models and uses those probabilities as weights. Bayesian model averaging has been literally hundreds of journal papers over the past decade or so; see e.g. Draper (1995), Hoeting et al. (1999), Clyde (1999), Clyde and George (2004). The literature has mostly been concerned with issues of interpretation and computation. Results about the large-sample behavior of Bayesian model-averaging schemes were found in Hjort and Claeskens (2003).

In this case, combining separate forecasts can improve forecasts. The concept and methodology of forecast combination were introduced by Bates and Granger (1969) in a seminal paper that has become a citation classic. Surveys and Discussions of some subsequent developments and applications by Clemen (1989), Granger (1989), and Diebold and Lopez (1996) testify to the wide spread interest that has developed in the topic. Newbold and Harvey (2002), Bates and Granger (1969) recommended that researchers should consider creating a combined forecast, possibly a weighted average of the individual forecast, when alternative forecasts are available. Granger and Ramanathan (1984) suggest the use of linear regressions to compute optimal combination weights; Diebold and Pauly (1990) propose a least squares weighted average and equal weighted combination, giving the methods Bayesian interpretations; and Stock and Watson (2004) suggest a factor model to extract the common forecast from a set of forecasts. But most studies still find that in majority of circumstances, simple methods like the equal weight averaging still performs as well as or even better than more sophisticated methods derived optimally using the variance-covariance structure of a set of historical forecast errors, see for example, Genre, Kenny, Meyler and Timmermann (2010). One endemic problem that has attracted little attention is the fact that many forecast data are incomplete or unbalanced in nature due to entry and/or exit of forecast experts. Suppose the combination methods are directly implemented on unbalanced panels without properly allowing for the unbalance structure of the data. Then a comparison of combined forecasts and related statistics are in general misleading because they are computed implicitly using different sets of balance panels. This is particularly problematic when the main aim is to compare the performance of different forecast combination methods.

In this chapter, the three forecasting exercises do not have this issue, since the same exact data sets are used in each exercise. Structural Model has the strength of forecasting the patterns. ARIMA and Trend line are closer to Actual compared to Structural Model in selected carrier and city-pair combination.

As noted, the use of a simple average has proven to do as well as more sophisticated approaches. Certainly, there are situations where one method is more accurate than another. If such cases can be identified in advance, simple averages would be inefficient.

3.2. Equal Weighted Model Averaging vs. Mean Square Weighted Model Averaging

In this chapter, I exam equal weighted average and mean square weighted average to see which one performs better than the other.

Chart 3.2.1.

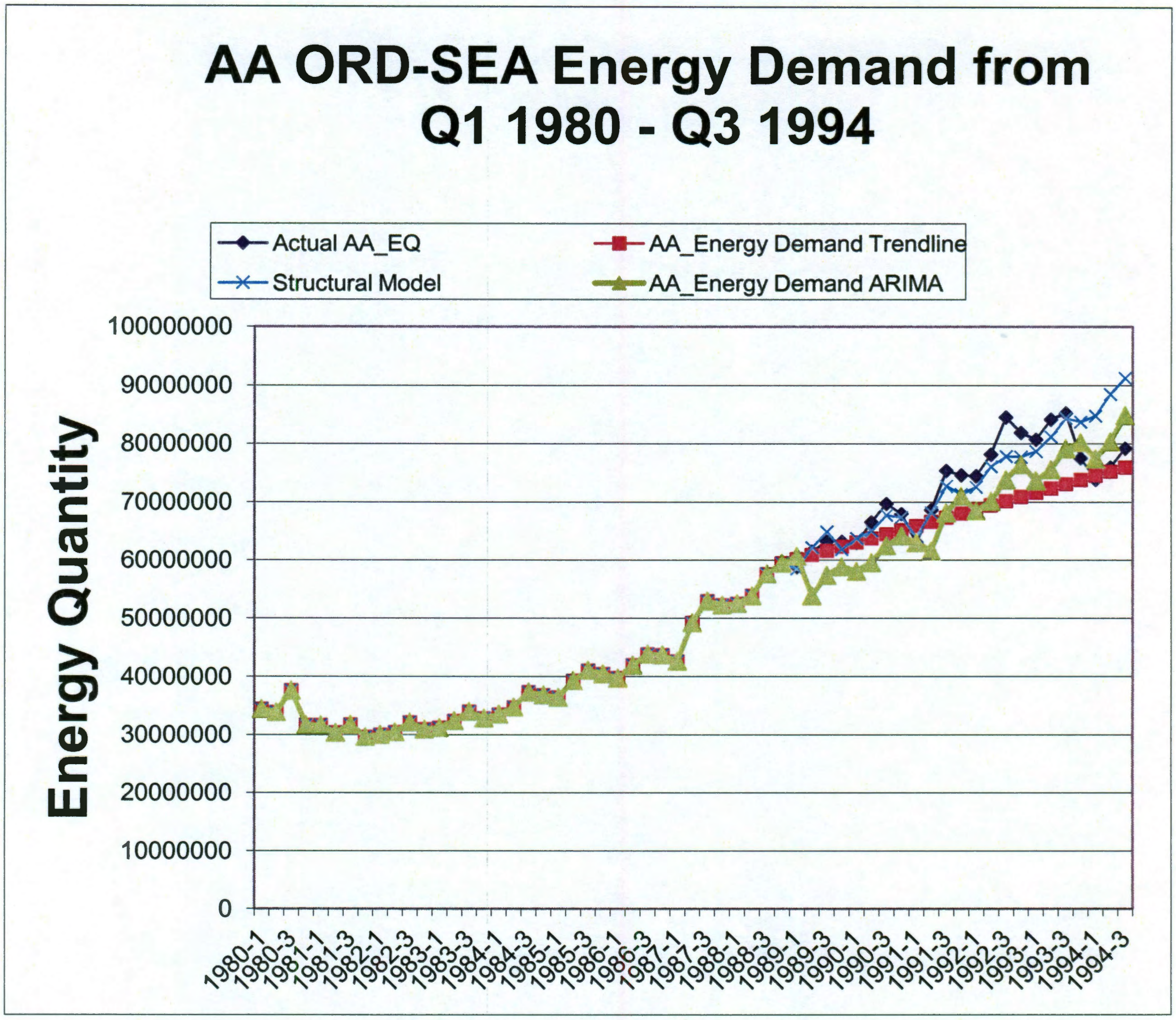
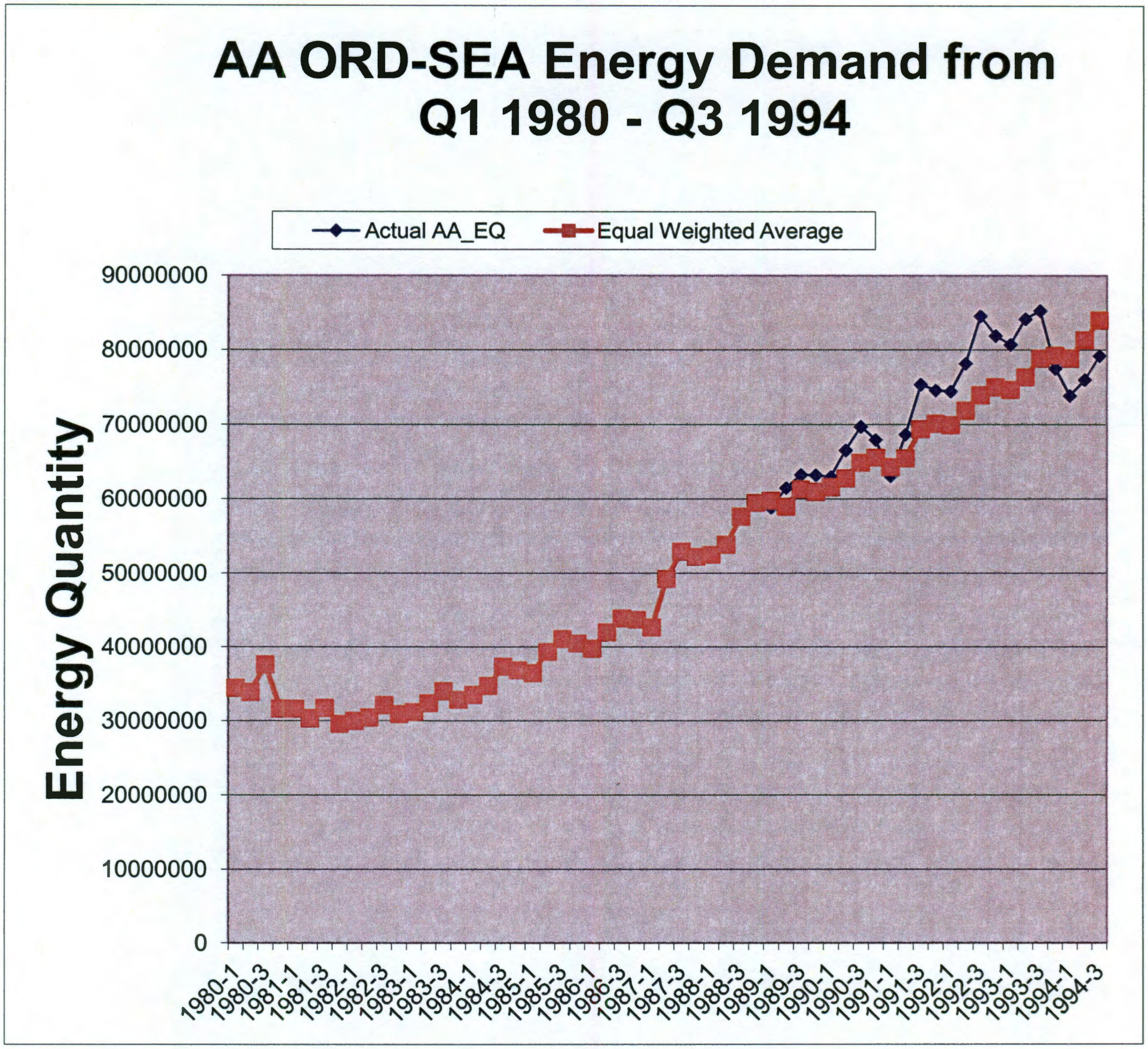


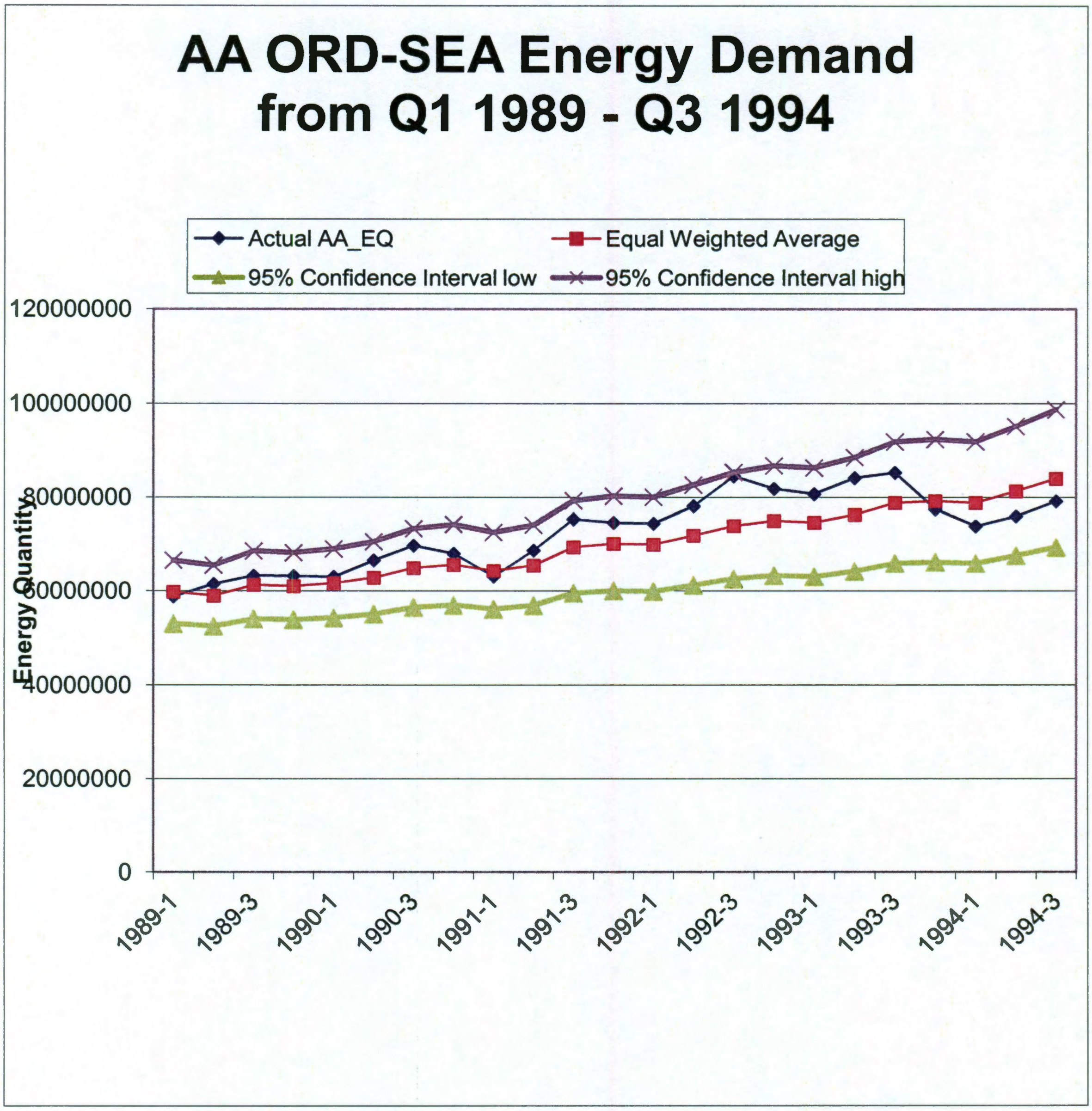
Chart 3.2.2 is equal weighted average of these three forecasts compared to Actual.

Chart 3.2.2.a



AA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
Equal Weighted Average
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
1987-1
1987-3
1988-1
1988-3
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.2.b



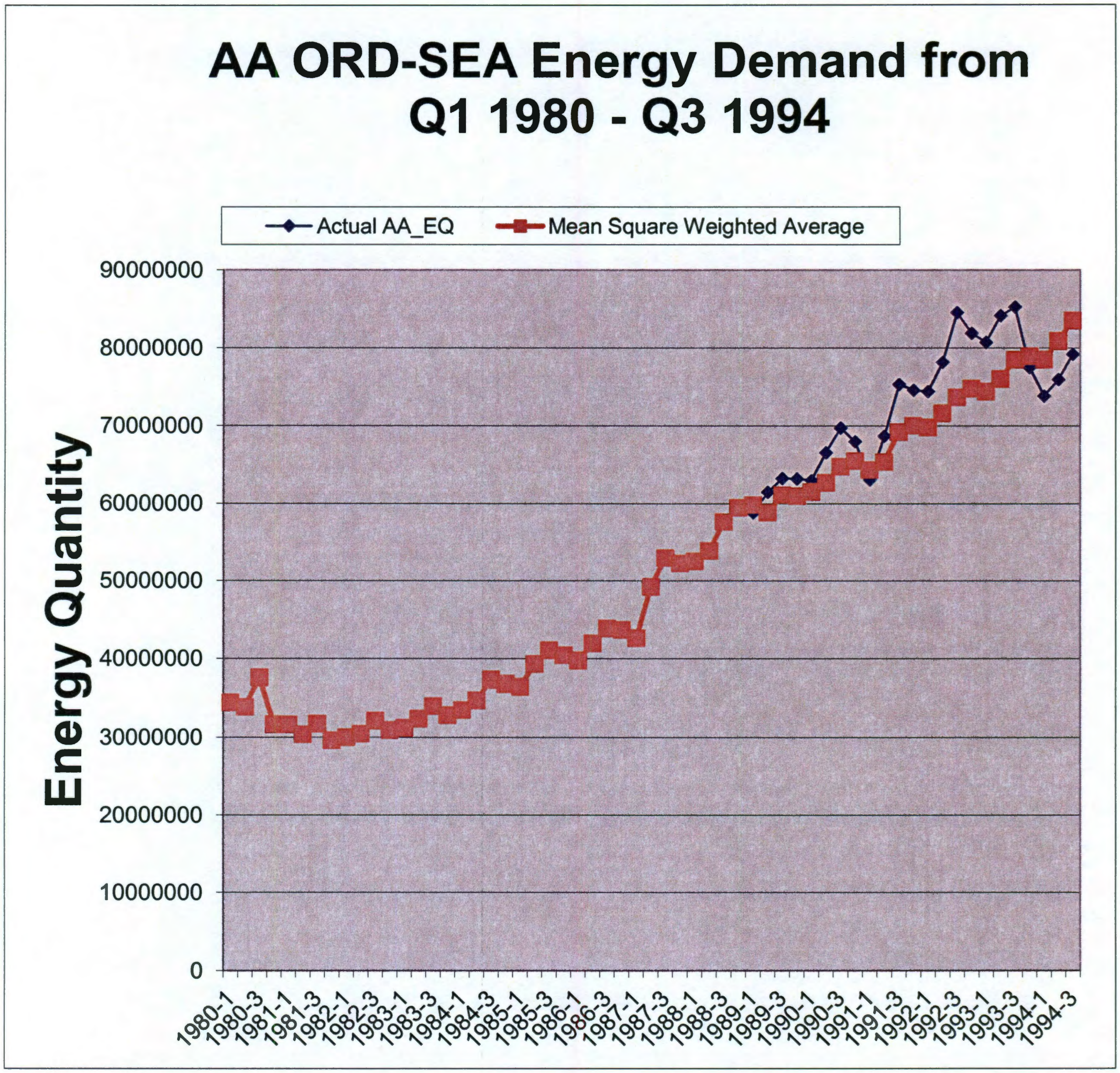
AA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual AA_EQ
Equal Weighted Average
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
120000000
100000000
80000000
60000000
40000000
20000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.3 is Mean Square Weighted Average of these three forecasts compared to Actual. The less the Mean Square is, the more weight it is given.

$$W_i = \frac{\sum_{i=1}^{3} MS_i - MS_i}{2 * \sum_{i=1}^{3} MS_i}$$

	MSE	Weight
AA Energy Demand Trend line	24,081,758,364,080	36%
AA Energy Demand ARIMA	26,460,659,407,815	34%
AA Energy Demand Forecast Structural Model	34,808,314,211,757	30%

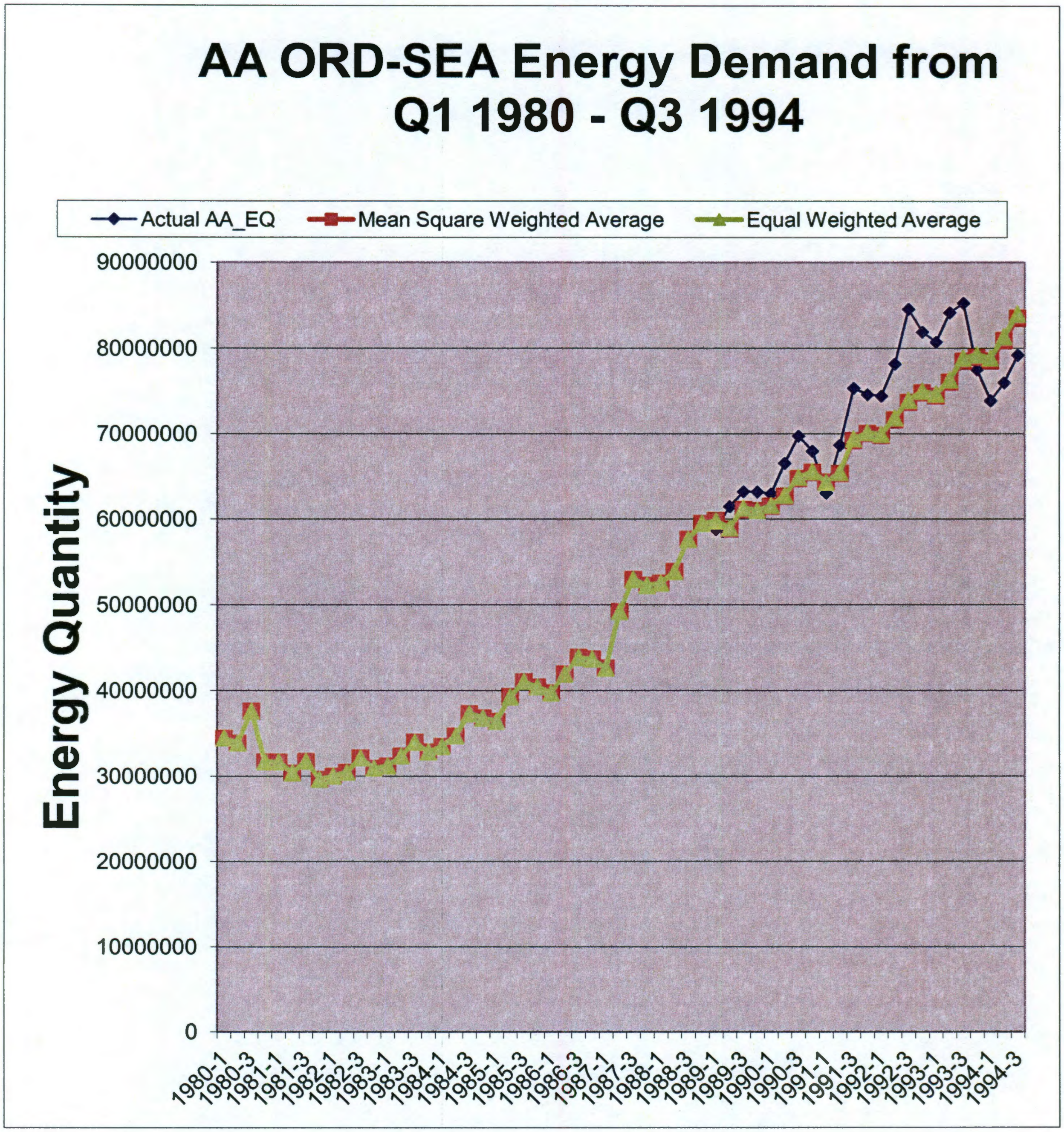
Chart 3.2.3



AA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
Mean Square Weighted Average
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
1987-1
1987-3
1988-1
1988-3
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.4 is the comparison of Equal Weighted Average and Mean Square Weighted Average. We can see Equal Weighted Average perform as good as Mean Square Weighted Average as forecasting AA ORD-SEA Energy Demand in the Q1 1980 –Q3 1994.

Chart 3.2.4



AA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
Mean Square Weighted Average
Equal Weighted Average
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
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1988-3
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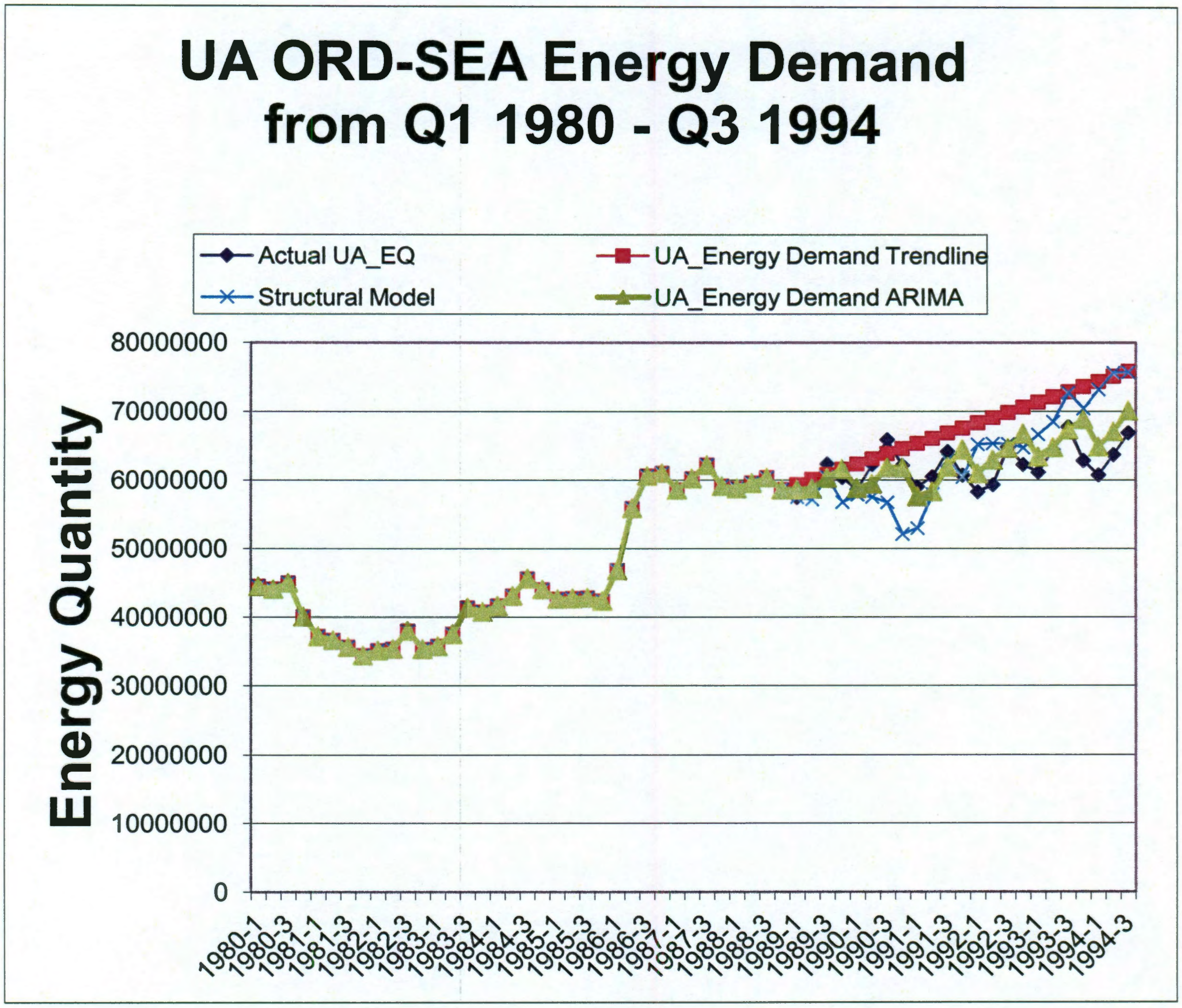
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.5 and Chart 3.2.6 are charts of UA ORD-SEA, the actual energy demand shows strong seasonal demand, reaching peaks in the 3rd quarters and touching bottoms in the 1st quarters. ARIMA Model predicts best among these three forecasts. When these three forecasts are combined together, a close to actual forecast is displayed. The majority actual fall in the 95% confidence of interval of equal weighted average of these three approaches.

Chart 3.2.5


UA ORD-SEA Energy Demand
from Q1 1980 - Q3 1994
Actual UA_EQ
UA_Energy Demand Trendline
Structural Model
UA_Energy Demand ARIMA
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
1985-3
1986-1
1986-3
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1989-3
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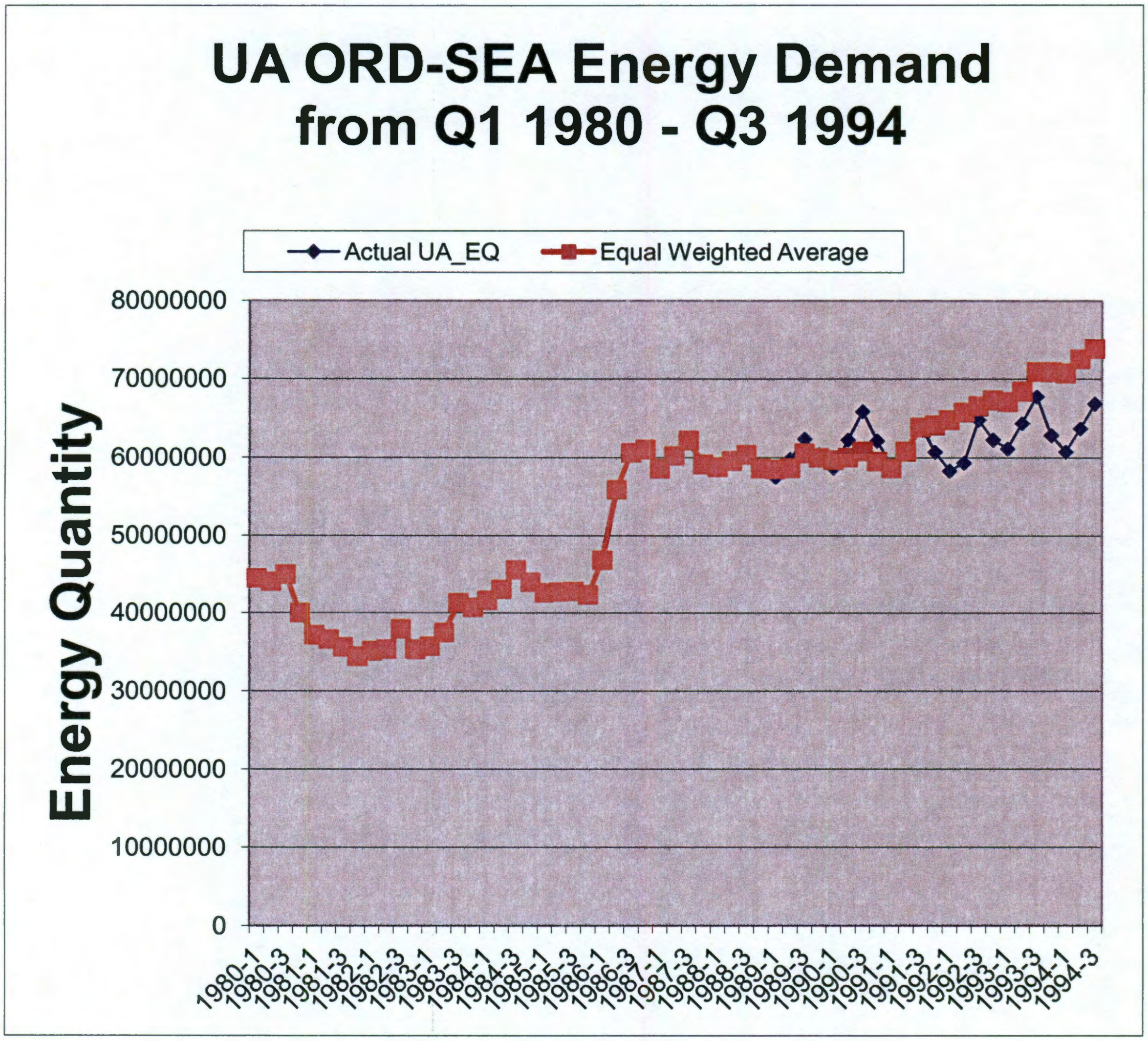
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.6.a



UA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual UA_EQ
Equal Weighted Average
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
1984-3
1985-1
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1986-3
1987-1
1987-3
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1989-3
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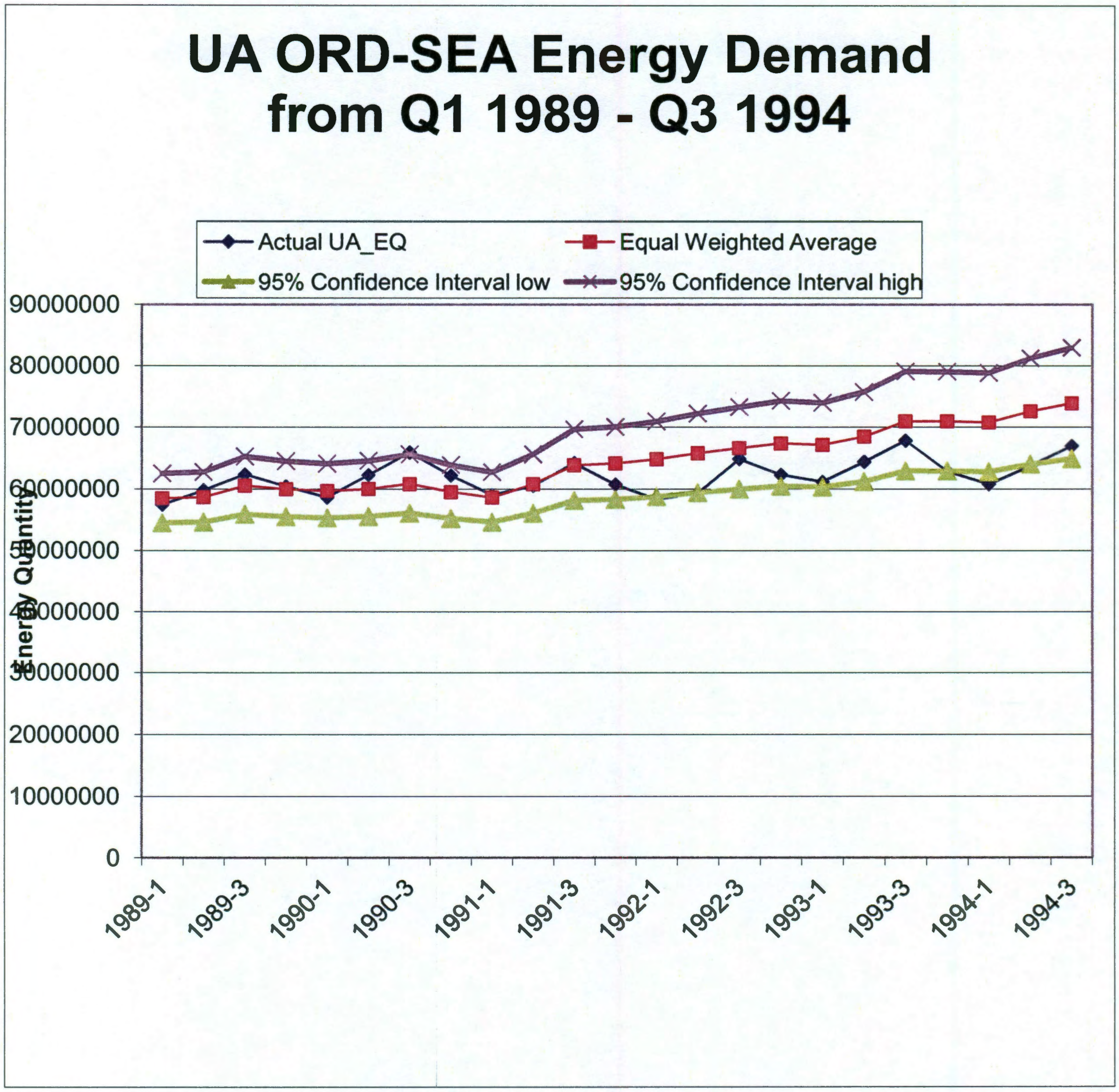
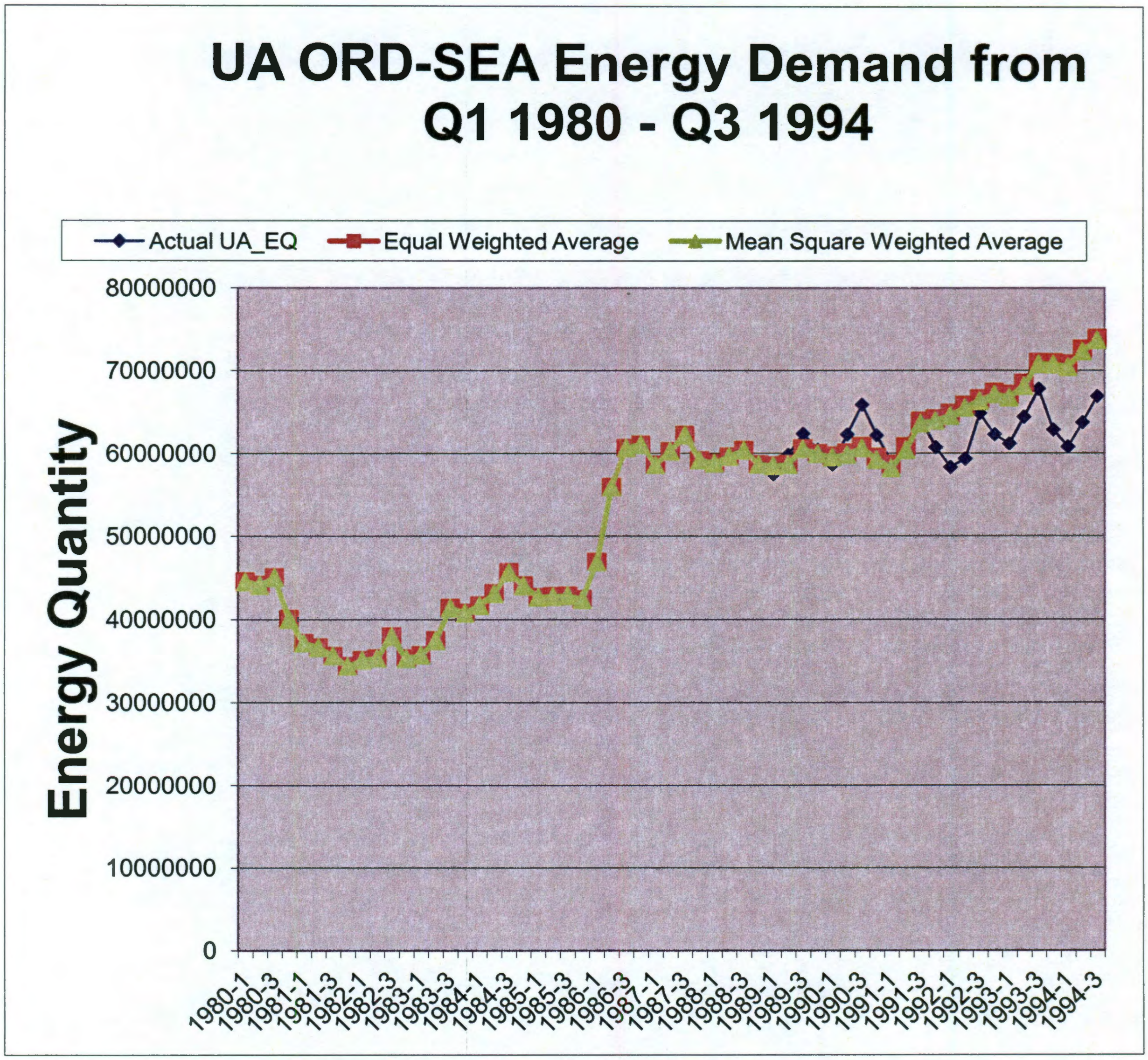
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.2.6.b


UA ORD-SEA Energy Demand from Q1 1989 - Q3 1994
Actual UA_EQ
Equal Weighted Average
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

	MSE	Weight
UA Energy Demand Trend line	13,433,421,751,023	28%
UA Energy Demand ARIMA	8,027,957,584,834	37%
UA Energy Demand Forecast Structural Model	9,320,565,941,776	35%

Chart 3.2.7


UA ORD-SEA Energy Demand from Q1 1980 - Q3 1994
Actual UA_EQ
Equal Weighted Average
Mean Square Weighted Average
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
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1988-3
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1993-1
1993-3
1994-1
1994-3

Chart 3.2.7 is the comparison of Equal Weighted Average and Mean Square Weighted Average of UA ORD-SEA Energy Demand from Q1 1980 –Q3 1994. We cannot see meaningful difference between the forecasts of Mean Square Weighted Average and Equal Weighted Average.

3.3. Model Averaging for ORD-SAN

As noted, an equal weighted Model Averaging has proven to do as well as more sophisticated approaches under certain circumstance. We here see how to apply different model averaging under different circumstance for city pair ORD-SAN.

From our Market Power chapter's findings, we know that in city-pair ORD-SAN, AA has 59% market power, while UA has 41%. In this city pair, AA has more market power than UA, which is vice versa in city-pair ORD-SLC we first discussed.

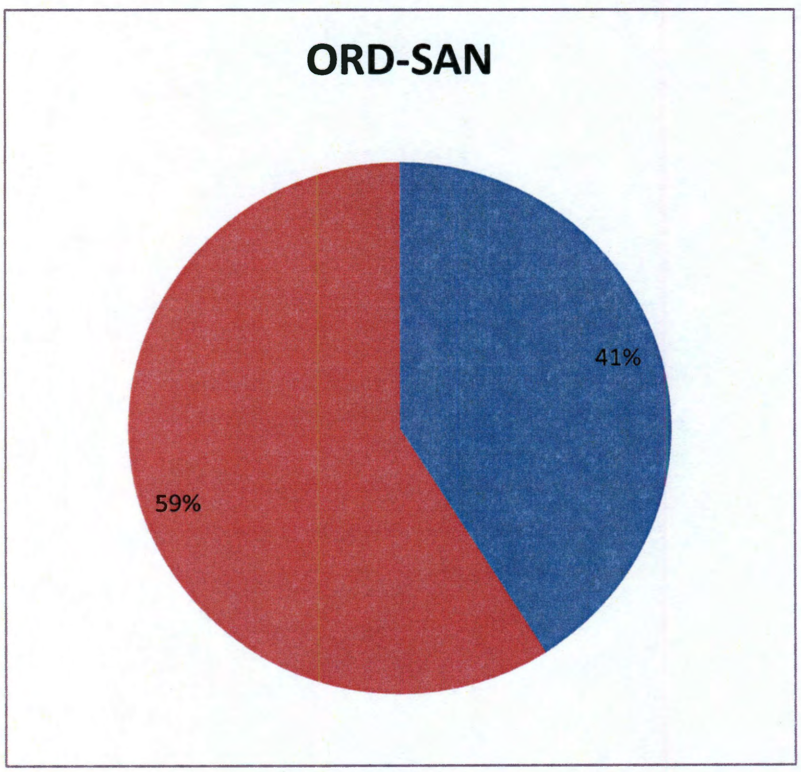
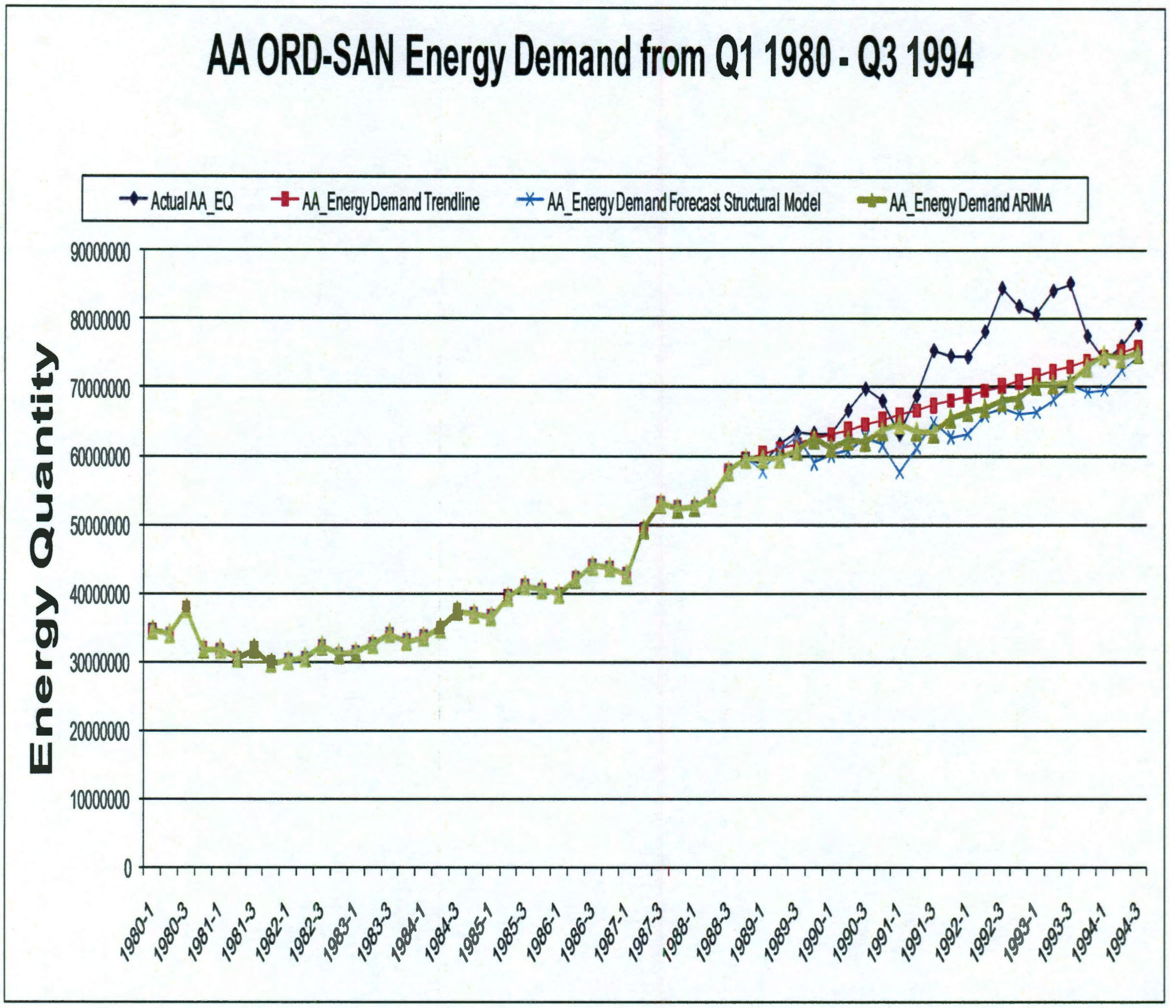


Chart 3.3.1


AA ORD-SAN Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
AA_EnergyDemand Trendline
AA_EnergyDemand Forecast Structural Model
AA_EnergyDemand ARIMA
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
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1990-3
1991-1
1991-3
1992-1
1992-3
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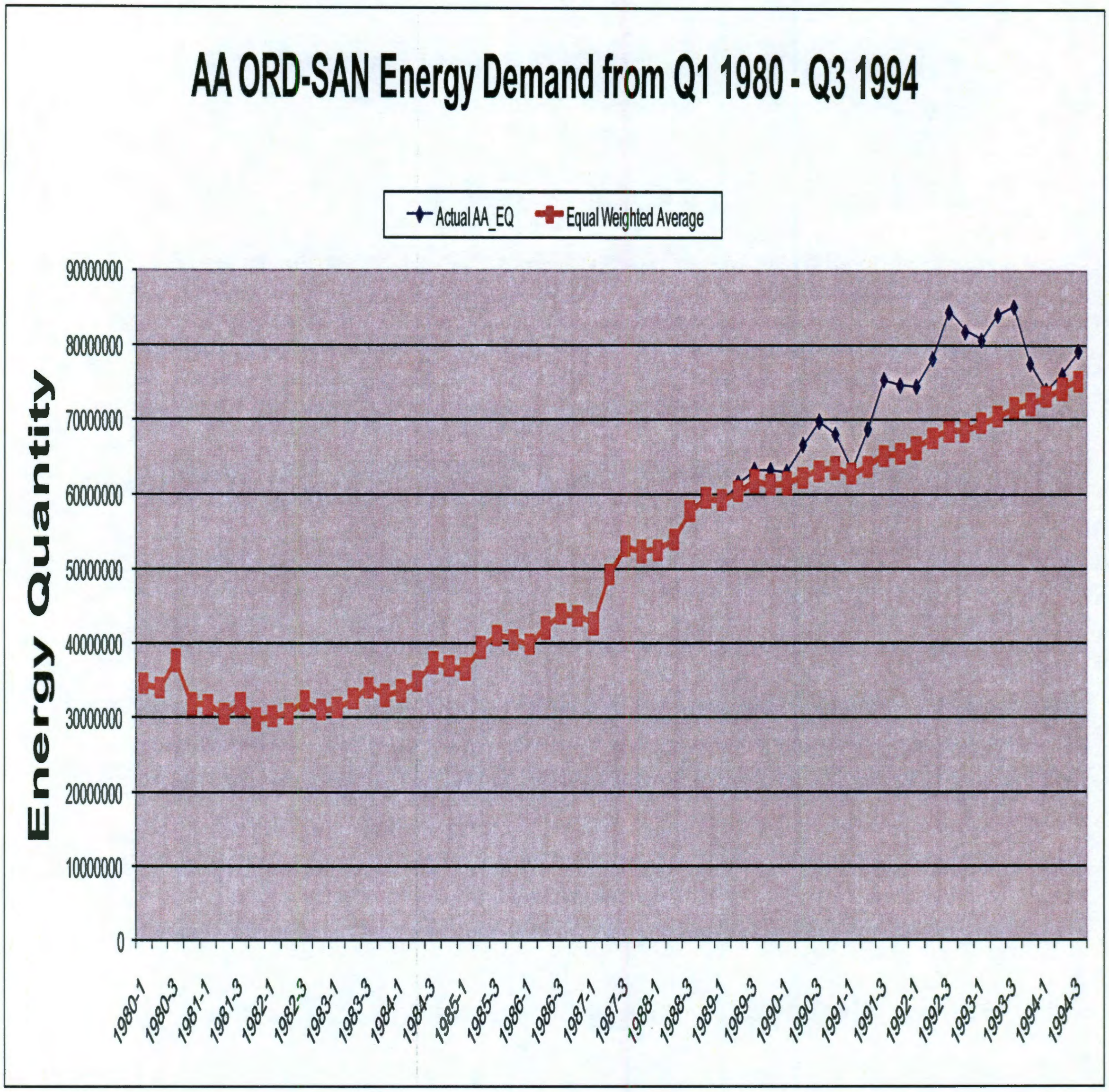
1993-3
1994-1
1994-3

For AA ORD-SAN, Structural Model, ARIMA and Trend line forecast are very close. Under this circumstance, assigning more weight to Structural Model can allow us have an average forecast that predicts turning points and seasonality. Chart 3.3.2 shows forecast of Equal Weighted Average. Chart 3.3.3 shows forecast of Optimized Weighted Average with 70% weight on Structural Model and 15% weight on ARIMA and Trend Line respectively.

Chart 3.3.2


AA ORD-SAN Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
Equal Weighted Average
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
1983-3
1984-1
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1985-1
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1986-3
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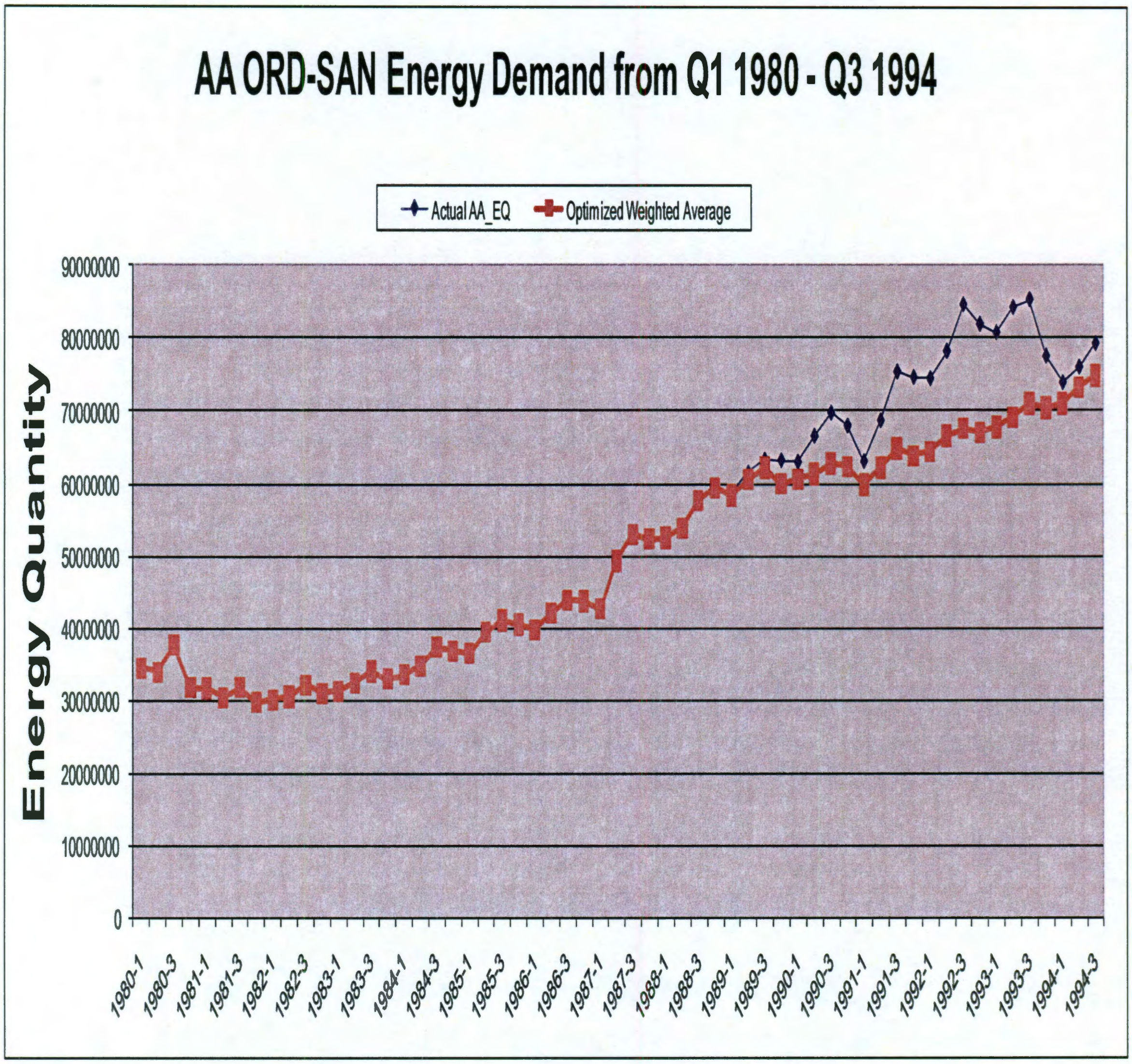
1993-3
1994-1
1994-3

Chart 3.3.3


AA ORD-SAN Energy Demand from Q1 1980 - Q3 1994
Actual AA_EQ
Optimized Weighted Average
Energy Quantity
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
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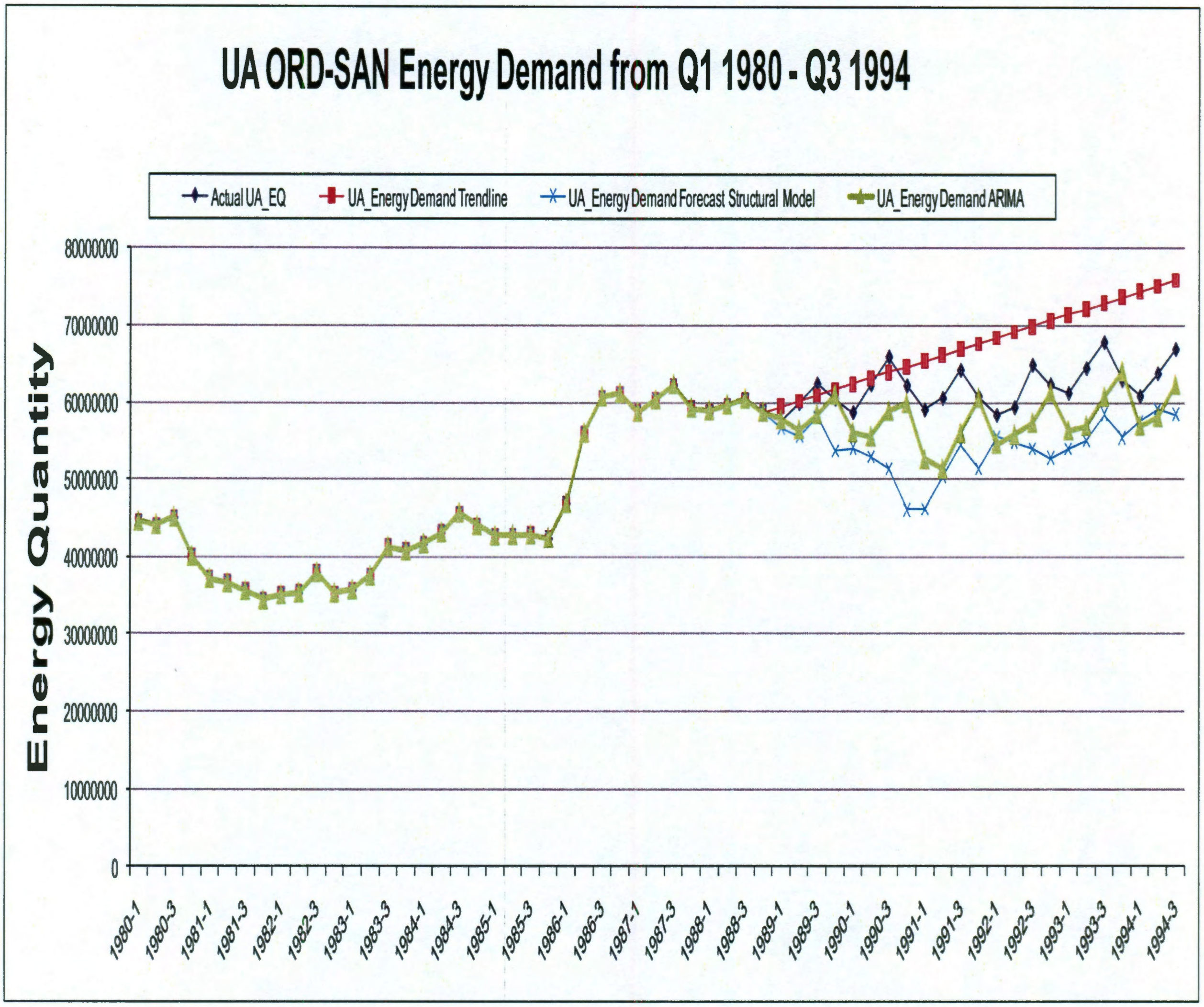
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
1992-1
1992-3
1993-1
1993-3
1994-1
1994-3

Chart 3.3.4 shows that these three forecasting approaches for UA ORD-SAN are significantly diverse. It is not convincing to pick just one approach. Under circumstances like this, simple Equal Weighted Average is the smart choice, which will allow you make a conclusion quickly and fairly. Chart 3.3.5 proves well.

Chart 3.3.4


UA ORD-SAN Energy Demand from Q1 1980 - Q3 1994
Actual UA_EQ
UA_Energy Demand Trendline
UA_Energy Demand Forecast Structural Model
UA_Energy Demand ARIMA
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
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1993-3
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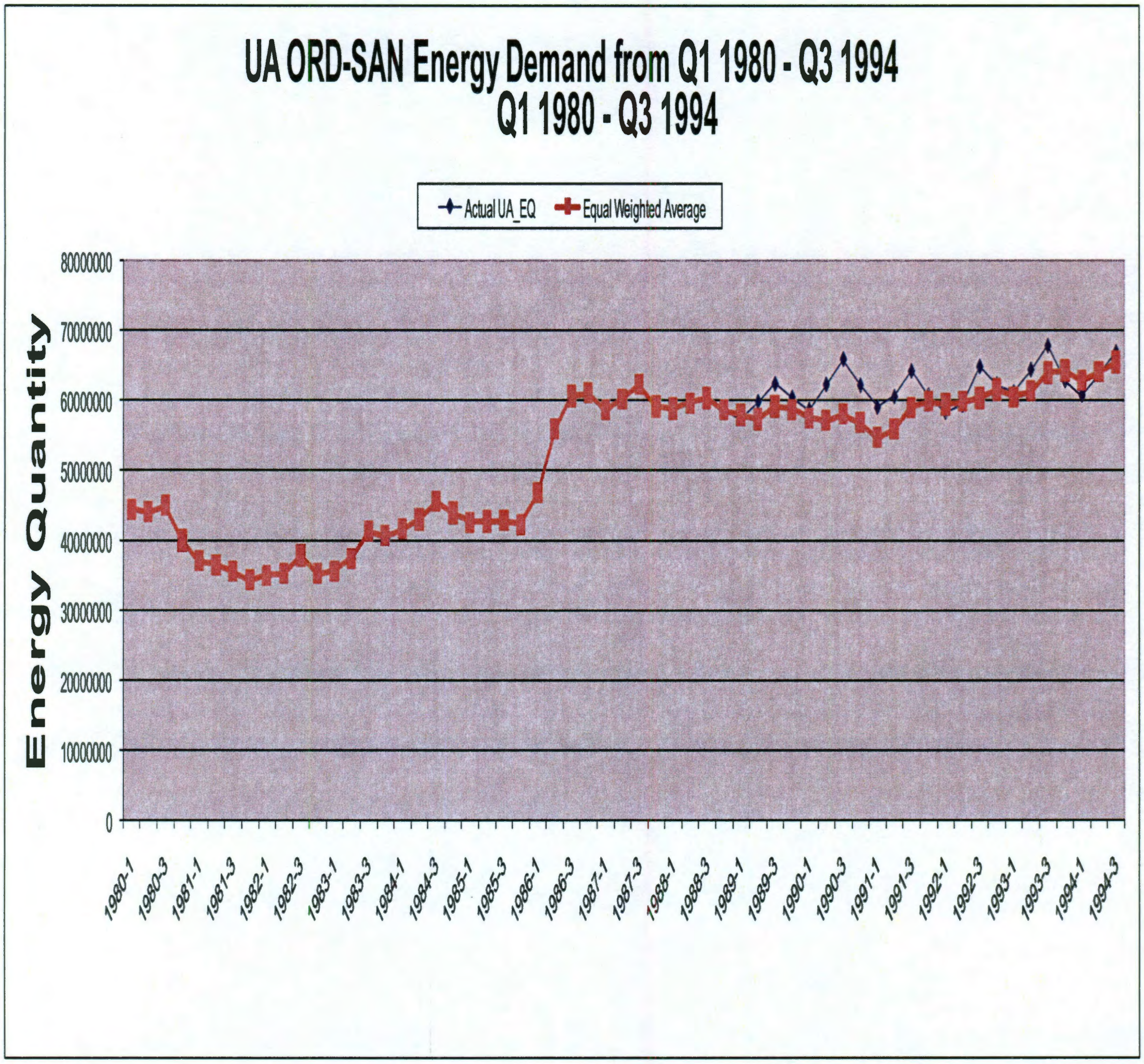
1994-3

Chart 3.3.5


UA ORD-SAN Energy Demand from Q1 1980 - Q3 1994
Q1 1980 - Q3 1994
Actual UA_EQ
Equal Weighted Average
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1980-1
1980-3
1981-1
1981-3
1982-1
1982-3
1983-1
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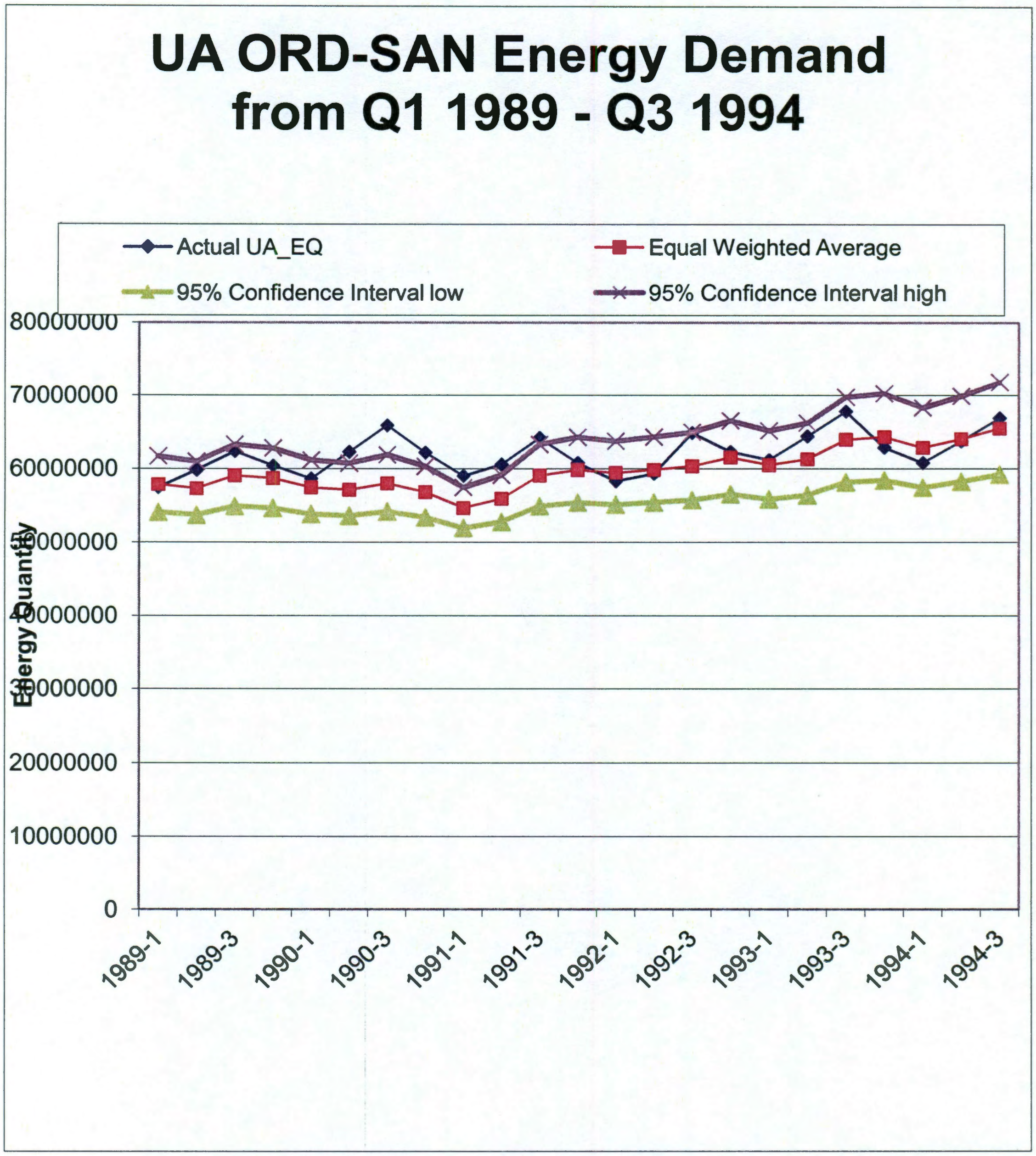
1993-3
1994-1
1994-3

Chart 3.3.6


UA ORD-SAN Energy Demand
from Q1 1989 - Q3 1994
Actual UA_EQ
Equal Weighted Average
95% Confidence Interval low
95% Confidence Interval high
Energy Quantity
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1989-1
1989-3
1990-1
1990-3
1991-1
1991-3
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1993-3
1994-1
1994-3

3.4. Conclusion

This thesis is motivated by the consolidation since the commercial airline industry was deregulated in 1978. We discussed the aviation industry for better understanding of the important milestones in the industry development. We thus turn our focus on the review of dynamic and static models of market power. After that, we developed of a dynamic model of collusion in airport-pair routes for selected U.S. airlines. We select four city-pairs that American (AA) and United (UA) are dominant players. The four city pairs are Chicago O'hare International (ORD)-San Diego International Airport (SAN), Chicago O'hare International (ORD)-Seattle-Tacoma International (SEA), San Francisco International (SFO) and Chicago O'hare International (ORD)-Salt Lake City International (SLC). We showed UA has a relatively larger market power share in ORD-SEA, ORD-SFO and ORD-SLC compared to AA, especially in ORD-SEA, where UA's market share is 63%. In city –pair ORD-SAN, AA has a relatively larger market share which is 59%. In this chapter, we only look at all the city pairs in which American and United are dominant firms. In future work, we can extend the chapter to examine richer empirical settings in which, among other things, the city-pair routes are not dominated by two firms and in which exit-entry is impacted by firm conduct and market conditions. Our general framework also appears to be an appropriate and feasible vehicle for examining market conduct in other industries where merger and acquisition activities may be subject to FTC or US department of Justice oversight.

We discuss the Energy industry for deeper understanding of current world Energy supply and demand. We then focus on the use of our structure model for purposes of forecasting energy demands. We discuss and utilize various forecasting approaches that combined forecasts using various weighting schemes and we utilize these as well as specific forecasts from our structure model, ARIMA time series and simple time trends. We showed that under different circumstances, different weighting schemes have different merits. Equal Weighted Average performs as good as Mean Square Weighted Average in forecasting AA ORD-SEA Energy Demand in the Q1 1980 –Q3 1994. UA ORD-SEA also shows that simple Equal Weight Average can predict as well as more sophisticated Mean Square Weighted Average. We also showed case like AA ORD-SAN, in which Structural Model, ARIMA and Trend line forecast are very close in Q1 1980 –Q3 1994, Optimized Weighted Average that with more weight assigned to Structural Model is better than Equal Weighted Average, while case like UA ORD-SAN, in which Structural Model, ARIMA and Trend Line predict in different directions, Equal Weighted Model Average provides a simple and fare forecast.

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